

RESIDENTIAL TIME-OF-USE PRICING – AN ECONOMETRIC ASSESSMENT

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ABSTRACT

Constrained electrical power systems and the long lead times needed for new capacity necessitate interim demand side management measures such as time-of-use (TOU) pricing. This form of electricity pricing has the potential to reduce system peak demand and thus improve the efficiency of power systems. Such time differentiated pricing mechanisms have been used successfully in the industrial and commercial sectors to shift demand out of the peak periods but have yet to be implemented in the residential sector in South Africa (SA). TOU schemes are based on the cost of supply and reflect, in part, the changes in short-run marginal costs. In contrast the conventional residential tariffs in SA are based on flat rate structures and recover long-run costs only. The analysis of the impact of such schemes, for both the utility as well as the customers, is gaining importance once more, particularly when most utilities are contemplating the implementation of smart systems and advanced metering infrastructures and the costs associated with this.

A recent TOU pilot project, HomeFlex, is analysed from an econometric point of view. Panel data sets for both treatment groups and the control group are obtained from the pilot project database for each customer in two separate experiments in two separate geographic areas. The Caves and Christensen approach is used and the constant elasticity of substitution functional form is chosen. Conditioning variables such as daily consumption per customer as well as climate effects are included in the ordinary least squares regression in order to establish the relationship between peak and off-peak consumption and the extent of the substitutability of these two commodities.

The elasticity of substitution estimates obtained for stage 1 of the analysis range from 0.339 to 0.384. The conditioning variables enter the analysis as modifiers to the estimates but their effect is insignificant. The stage 2 estimates range from 0.457 to 0.518. The effect of the conditioning variables is also statistically insignificant at this stage. The effect of the daily and weekly price ratio is therefore the primary factor in determining the response of customers to TOU pricing in the HomeFlex project.

LIST OF ACRONYMS

°C	Degrees Centigrade
\$	US Dollar
C\$	Canadian Dollar
€	Euro
c/kWh	Cents per Kilowatt Hour
CAC	Central Air Conditioner
CDD	Cooling Degree Days
CES	Constant Elasticity of Substitution
CPP	Critical Peak Pricing
DME	Department of Minerals and Energy
DPP	Dynamic Peak Pricing
DSM	Demand Side Management
EDF	Électricité de France
GCC	Gulf Cooperation Council (countries)
GL	Generalised Leontief
HDD	Heating Degree Days
HDH	Heating Degree Hours
HVAC	Heating, Ventilating and Air Conditioning
HWC	Hot Water Convertor / Cylinder
kWh	Kilowatt Hour
LSM	Living Standards Measure
MS	Microsoft
OLS	Ordinary Least Squares
PCT	Programmable Communicating Thermostats
PSE&G	Public Service Electric and Gas Company
R	Rand
RPP	Regulated Price Plan
RTP	Real-Time Pricing
SA	South Africa
TOD	Time of Day
T2	Two-part Tariff (Eskom's HomeFlex pilot)
T3	Three-part Tariff (Eskom's HomeFlex pilot)
TOU	Time-of-Use

US

United States

TABLE OF CONTENTS

CHAPTER ONE : INTRODUCTION AND BACKGROUND	1
1.1 Introduction.....	1
1.2 Background to the problem	2
1.3 The research problem.....	4
1.4 The research question.....	4
1.5 The research objective.....	4
1.6 The hypothesis.....	5
1.7 The importance of this study.....	5
1.8 Organisation of this dissertation.....	5
 CHAPTER TWO : LITERATURE REVIEW	 7
2.1 Introduction.....	7
2.2 The theory of price elasticity of demand.....	7
2.3 Price and income elasticity estimates for South Africa	10
2.4 Price and income elasticity estimates for other developing countries	11
2.5 Summary of international price and income elasticity estimates	12
2.6 Factors that influence residential customers price responsiveness	13
2.6.1 Appliance ownership.....	13
2.6.2 Household demographics.....	15
2.6.3 Income	15
2.6.4 Alternative energy sources	16
2.6.5 Climatic conditions.....	18
2.6.6 Tariff design.....	18
2.7 The current residential electricity tariffs in South Africa.....	19
2.8 Price elasticity studies specific to time-varying pricing tariffs	24
2.8.1 The elasticity of substitution.....	25
2.8.2 Factors that affect customer response to TOU pricing.....	25
2.8.2.1 Appliance ownership	25
2.8.2.2 Climatic conditions	27
2.8.2.3 Household characteristics	27
2.8.2.4 Income.....	28
2.8.2.5 Total consumption	28
2.8.2.6 Tariff design	29
2.8.2.7 Participation level.....	30
2.9 International experiences with experimental residential tariffs	31
2.9.1 Anaheim Public Utilities – California.....	31
2.9.2 Automated Demand Response System Pilot – California.....	32
2.9.3 State-wide Pricing Pilot – California	32
2.9.4 XCEL Energy TOU Pilot – Colorado.....	33
2.9.5 Gulf Power Select Programme – Florida	33
2.9.6 Électricité de France – France	34
2.9.7 Idaho Residential Pilot Programme – Idaho.....	34
2.9.8 Energy Smart Pricing Plan – Illinois.....	35
2.9.9 Ameren UE CPP Pilot – Missouri.....	36
2.9.10 GPU Pilot – New Jersey.....	37
2.9.11 PSE&G Residential Pilot Program – New Jersey	38
2.9.12 Energy Australia’s Network Tariff reform – New South Wales	39
2.9.13 Ontario Energy Board’s Smart Price Pilot – Ontario, Canada.....	40
2.9.14 Puget Sound Energy TOU programme – Washington	41
2.9.15 The Olympic Peninsula Project – Washington.....	41
2.10 Conclusion	42

CHAPTER THREE : EXPERIMENTAL TIME-OF-USE TARIFF	45
3.1 Introduction.....	45
3.2 Pilot tariff design.....	45
3.3 Engineering analysis of the impact of the HomeFlex tariff.....	47
3.4 Conclusion	51
CHAPTER FOUR : METHODOLOGY FOR ECONOMETRIC ANALYSIS	52
4.1 Introduction.....	52
4.2 The theoretical framework.....	52
4.3 The model specification and choice of functional form	55
4.4 Summary of the Caves and Christensen three-stage model.....	58
4.5 Conclusion	59
CHAPTER FIVE : DATA FOR ECONOMETRIC ANALYSIS	60
5.1 Introduction.....	60
5.2 Panel data sets	60
5.3 Customer load data.....	61
5.4 TOU electricity prices.....	64
5.5 Customer characteristics.....	65
5.6 Climate variation data	
5.7 Summary of econometric notations.....	69
5.8 Conclusion	70
CHAPTER SIX : ANALYSIS AND DISCUSSION OF RESULTS	72
6.1 Introduction.....	72
6.2 Techniques used in the analysis	72
6.3 Testing the hypothesis.....	73
6.4 Estimates of stage 1	73
6.4.1 Estimates obtained with no conditioning variables.....	74
6.4.2 Estimates obtained with conditioning variables	74
6.4.2.1 Daily range consumption conditioning variables	75
6.4.2.2 Climate variation conditioning variable	77
6.4.3 Summary of stage 1 estimates	78
6.5 Estimates of stage 2.....	80
6.5.1 Estimates obtained with no conditioning variables	80
6.5.2 Estimates obtained with conditioning variables	81
6.5.3 Summary of stage 2 estimates	82
6.6 Estimates of stage 3.....	84
6.7 Interpreting the results.....	84
6.8 Using the model to estimate customer response to TOU pricing.....	85
6.9 Comparison to other studies	86
6.10 Load curtailment – benefits to the utility.....	87
6.11 Welfare effects – impact on the customer	90
6.12 Conclusion	91
CHAPTER SEVEN : CONCLUSION AND RECOMMENDATIONS	94
7.1 Introduction.....	94
7.2 Limitation of this study.....	94
7.3 Recommendations	95
7.4 Conclusion	95
REFERENCES.....	97

APPENDICES.....100

LIST OF FIGURES

Figure 1-1: Capacity and demand forecast for SA (2006 to 2026)	3
Figure 2-1: Relationship between supply and demand with two different demand curves.....	9
Figure 2-2: Impact of a shift in supply curves	9
Figure 2-3: Impact of a shift in demand curves	10
Figure 2-4: SA household expenditure and total number of households in 2005	16
Figure 2-5: Illustration of a flat rate tariff	21
Figure 2-6: Illustration of an inclining block tariff.....	20
Figure 2-7: Illustration of a TOU tariff	23
Figure 2-8: Illustration of a CPP tariff	24
Figure 2-9: Peak period pricing and commodities specified for analysis	29
Figure 3-1: Eskom-defined time periods.....	46
Figure 3-2: Response by Sandton customers to TOU rates – high season, weekday profile.	48
Figure 3-3: Response by Sandton customers to TOU rates – high season, weekend profile.	49
Figure 3-4: Response by Tableview customers to TOU rates – high season, weekday profile	50
Figure 5-1: Average temperatures (Winter 2001).....	68
Figure 5-2: Average HDDs (Winter 2001)	69
Figure 6-1: Sandton treatment customers’ daily use shares compared to control customers’ daily use shares	88
Figure 6-2: Tableview treatment customers’ daily use shares compared to control customers’ daily use shares	89
Figure 6-3: Sandton and Tableview improvement in use shares and load factor.....	89
Figure 6-4: The welfare impact on Sandton customers.....	90
Figure 6-5: The welfare impact on Tableview customers.....	91

LIST OF TABLES

Table 2-1: Estimated marginal effects of appliances on consumption.....	14
Table 2-2: Substitution elasticity estimates – GPU pilot	38
Table 2-3: Price elasticity estimates – Energy Australia.....	40
Table 3-1: Alignment of HomeFlex to defined time periods	46
Table 3-2: HomeFlex experimental energy charges	47
Table 5-1: HomeFlex database key Tables	62
Table 5-2: Example of raw data file generated by query	63
Table 5-3: Example of final customer load dataset and fields	64
Table 5-4: TOU energy rate prices for HomeFlex	64
Table 5-5: TOU energy rate prices – econometric notation.....	65
Table 5-6: HomeFlex customers’ consumption averages (Winter 2001).....	66
Table 5-7: Definition of range consumption variable	66
Table 5-8: Average HDH (Winter 2001)	67
Table 5-9: Data parameters for econometric analysis.....	69

DEFINITIONS

HomeFlex	An experimental time-of-use pricing pilot project conducted by Eskom from 1998-2003.
Off-peak period	A period of the day in which electrical demand is low – typically the periods between peak periods, 10h00 to 18h00 and 20h00 to 07h00 (Eskom-defined periods).
Peak period	A period of the day in which electrical demand is high. There are typically two peak periods in a day – a morning peak, 07h00 to 10h00, and an evening peak 18h00 to 20h00 (Eskom-defined periods).
Smart meter	An electricity meter that allows for the measurement and storage of energy on a continuous basis. Two-way communication between the consumer and licensee provides for remote load management.

CHAPTER ONE : INTRODUCTION AND BACKGROUND

1.1 Introduction

Electricity is considered a basic service just like any other commodity and consumers consider it an essential service (Al-Faris, 2002). This is further substantiated by the high premium consumers place upon access to electricity, as suggested by the amount they spend on this commodity, as a portion of household disposable income (Martins, 2006). Electricity provides many conveniences we associate with a decent standard of living such as cooking, hot water and lighting. Its use can also be described as 'discretionary' as suggested by differences in levels of consumption and patterns of use across income strata. Lifecycle stages and lifestyles also alter perceptions as to what constitutes 'essential' consumption and thus potentially limits marginal use changes in response to price changes (Langmore and Dufty, 2004)

Electricity is important to health and societal wellbeing and there are public expectations that access to this commodity will be available for all residential customers. As suggested by a number of studies on the effect of changes in income and the resultant changes in consumption of electricity, as income levels increase so too do levels of electricity consumption. In South Africa (SA), as more homes become electrified, less reliance has been placed on alternative fuels, e.g., paraffin, for lighting as a greater proportion of households have increased their use of electricity for this purpose in 2001 (69.7%) as compared to 1996 (57.3%) (Statistics South Africa, 2001).

Residential electricity demand in SA has grown at an average rate of 4.9% per year from 1990 to 2005. This sector is expected to contribute 19.3% to the total electricity demand by 2010 (National Energy Regulator of South Africa (NERSA), 2005). The Energy White Paper of 1998 states that as residential consumption levels increase, households will be given the incentive to shift to more sophisticated cost reflective tariffs. These will aim to provide a strong signal to residential customers to choose affordable and appropriately rated supply options (Department of Minerals and Energy (DME), 1998).

Time-of-use (TOU) rates are used extensively in the electric power industry to provide a better match between the price residential customers pay for electricity and the time-varying

marginal costs of providing this service. Fluctuations in demand over the day, together with capacity constraints, create variations in both the marginal costs of generation and the expected marginal costs due to generator outages. Efficiency dictates that these variations in costs be conveyed to the consumers in the form of time-varying rates (Baladi et al., 1998).

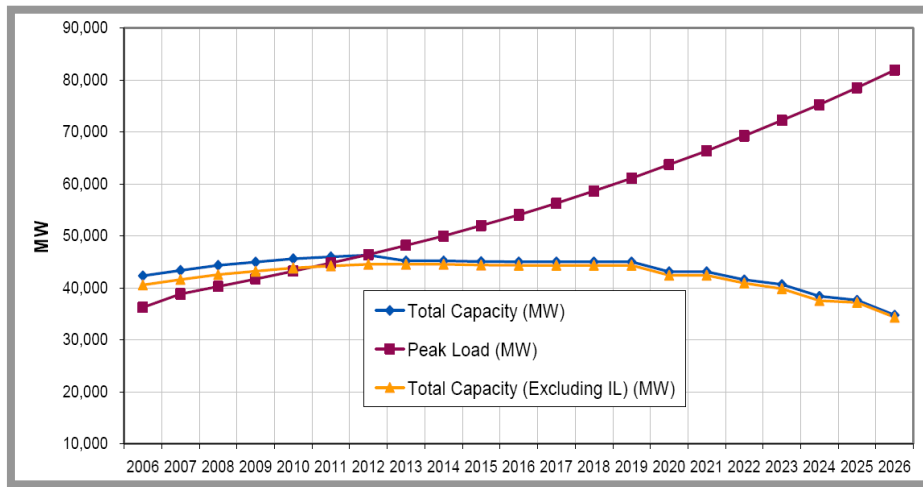
In the 1970s, electricity prices in the United States (US) increased significantly primarily because of the increase in residential consumption due to space heating and cooling appliances been purchased. This load growth had long- and short-term implications. In the short term, more oil and gas peaking plants had to be dispatched to meet demand, thereby increasing short-term marginal operating costs. In the long term more capacity was needed, thereby increasing capacity costs. The effect of this was higher prices for customers. TOU pricing was then proposed as an alternative to traditional time-invariant pricing for two main reasons: 1) these tariff structures more accurately reflect the true time-varying costs of supplying electricity and thus provide more efficient allocation of existing capacity, and 2) TOU provides an incentive for customers to shift their consumption from peak to off-peak periods. The net effect of which is expected to slow the rising electricity prices (Faruqui and Malko, 1983).

SA also faces an energy crisis and interim Demand Side Management (DSM) measures have been proposed until new generation capacity comes on line in 2012. Amongst these measures are TOU tariffs for the residential market (Eskom, 2008). In order to implement such tariffs, 'smart systems' and advanced metering infrastructures are needed to allow the collection, processing and billing of data. Eskom as well as several large municipalities are considering smart metering and smart systems in order to comply with the requirements in the Electricity Regulations Act (4/2006) – Schedule 2(d) of the Act states that an end user or customer with a monthly consumption of 1000 Kilowatt hours (kWh) or more must have a smart system installed by January 2012 (DME, 2008).

1.2 Background to the problem

Electricity demand in SA has increased at an average rate of 3.09% per year from 1995 to 2006 and the forecasted growth in demand is expected to increase to an average rate of 4.17% per year up until 2026 (see Appendix 1A and 1B). This steady growth in demand is expected to outstrip supply by 2012 as shown in Figure 1 (NERSA, 2005).

Figure 1-1: Capacity and demand forecast for SA (2006 to 2026)



Source: NERSA (2005)

Peak demand in SA normally occurs in the winter months and a large portion of this can be attributed to residential loads such as electric space heating. The current high load factor of 75%, which can also be attributed to typical residential consumption patterns, is an indicator of relative inefficiency in demand side consumption in relation to the supply side and implies that a high reserve margin is needed in order for SA to meet international reliability standards. In particular, residential electricity prices are based on long-run marginal costs and do not reflect the short-run marginal changes in supply costs associated with a system that has a high load factor. Residential tariffs are thus generally flat rate tariffs providing no adequate pricing signal to consumers to alter consumption patterns based on time-varying costs of supply (NERSA, 2008).

The steady increase in demand over the years further exacerbated the events that led to the numerous load-shedding events in SA during January 2008. These events were mainly due to Eskom experiencing primary fuel problems and unexpected generator outages. The lack of necessary infrastructure up to this point was due to previous Government decisions to allow independent power producers into the market – said producers had not yet materialised or provided any infrastructure (Eskom, 2008). In its report on the load-shedding incidents of January 2008, NERSA recommended, amongst others, that time- and cost-differentiated pricing be included in the National Retail Tariff Guidelines and be made available to residential customers by Distribution licensees (NERSA, 2008).

1.3 The research problem

Though time- and cost-differentiated pricing has been proposed as a DSM initiative, the research in this field is very limited in SA. Price elasticity studies were conducted and documented by, amongst others, Pouris in 1987 and Whittaker and Barr in 1989 (both in Whittaker and Barr, 1989) and Zarimba in 2008. These studies, however, focus on the long-run price elasticity of demand for electricity in SA. Research on TOU residential pricing and the extent to which customers will respond to such pricing initiatives in SA was not found in the literature – a research gap was identified. Furthermore, no econometric studies in this regard were found. Any comparison to studies done by other utilities is therefore not possible.

1.4 The research question

Will residential customers in SA respond significantly to short-term price differentials, as is the case in TOU pricing, or are there other factors that contribute to customers' responses?

1.5 The research objective

In order to follow the econometric analysis approach adopted by most utilities in estimating the response to TOU pricing experiments, this study will analyse the data from a recent TOU experiment conducted by Eskom – the HomeFlex residential pricing pilot project. The project tested the responses of 272 residential customers to TOU pricing in three different areas across SA. The experiment involved a control group on standard electricity tariffs as well as treatment groups on 2- and 3-part tariffs. The analysis followed a purely engineering approach for which treatment customers' responses were compared to control customers' responses. No price elasticity studies were done in this regard.

The objective of this dissertation is to substantiate the results obtained from the engineering approach with an econometric assessment using the same data. The study thus follows a quantitative approach. In doing so, this dissertation attempts to identify an acceptable methodology for the analysis of future TOU tariff pilot projects as well as implementation projects by Eskom and other utilities in the country. The key objective is to identify a suitable methodology for the assessment of TOU pricing, and not necessarily conduct a precise analysis. A further understanding of the factors that influence residential electricity demand under TOU rates is also expected to come from this study.

1.6 The hypothesis

A preliminary literature review on the econometric analysis of time-varying tariff schemes identified the price differential between peak and off-peak prices as having a greater effect on customer response than factors such as appliance ownership and climate variations (Caves et al., 1984a). This was taken as a starting point for this study and the following was thus hypothesised:

Hypothesis

The extent of the response of residential customers to TOU tariff pricing is determined primarily by the peak to off-peak price differential of the tariff.

1.7 The importance of this study

This study is important because it attempts to identify a generally acceptable methodology for the assessment of TOU pricing response by residential customers, in the absence of any other studies in this regard for SA. This is in light of the proposed investment decisions to be taken, by Eskom as well as some of the larger municipalities in SA, on metering systems required to facilitate such pricing schemes in the residential sector. In particular, the requirements laid out in the Electricity Regulations Act (4/2006) which specifies TOU metering by 2012 for all customers with a monthly consumption of more than 1000kWh. Investment in infrastructure costs is expected to be significant. A more comprehensive understanding of the response factors to TOU pricing will assist the utility in making such investment decisions.

1.8 Organisation of this dissertation

This dissertation is organised as follows:

Chapter one presents an introduction to the dissertation and a background to the research problem. The research objectives and the hypothesis to be tested are included in this chapter. **Chapter two** presents the review of the literature. **Chapter three** presents a review of the HomeFlex TOU experimental tariff pilot project undertaken by Eskom. **Chapter four** presents the methodology, identified in the literature, for the econometric analysis of TOU pricing. **Chapter five** identifies the data that was required for analysis as well as the variables needed to testing the hypothesis. **Chapter six** presents the econometric analysis of

the data. **Chapter seven** concludes this dissertation and makes recommendations for future research.

CHAPTER TWO : LITERATURE REVIEW

The previous chapter introduced the dissertation by identifying the research problem, the research objective and the hypothesis to be tested. This chapter presents the literature review.

Section 2.1 presents a brief introduction to the chapter. **Section 2.2** reviews the classic consumer supply and demand theory that relates specifically to the price elasticity of demand for electricity. **Section 2.3** identifies the studies undertaken on the price elasticity of demand for SA. **Section 2.4** presents the findings from the price elasticity studies done in other developing countries and a brief summary of these is presented in **Section 2.5**. **Section 2.6** identifies the factors that influence residential customers' responses to electricity pricing. **Section 2.7** presents a review of the type of tariffs for the residential sector. **Section 2.8** presents a review on the price elasticity studies specific to time-varying rates. **Section 2.9** then presents the international experiences with experimental tariffs and **Section 2.10** concludes this chapter.

2.1 Introduction

This chapter begins with some of the economic theory describing the demand for electricity. Included in the review are selected studies on the short- and long-term price elasticity estimates for both developed and developing countries, including SA. The objective is to identify the literature that describes the theory, methodology and data that is required for the econometric assessment of TOU pricing as well as the factors that determine customer responsiveness to changes in electricity prices. In doing so the review attempts to identify previous studies in this regard as well as the approaches that were taken. A review of some of the selected studies on residential time-varying rates concludes this chapter.

2.2 The theory of price elasticity of demand

Price elasticity of demand is the quantitative measure of consumer behaviour that indicates the quantity of the demand for a product or service depending on its increase or decrease in price, and is a useful measure of the impact of price changes on quantity consumed (Dolan and Simon, 1996). The price elasticity of demand is expressed as:

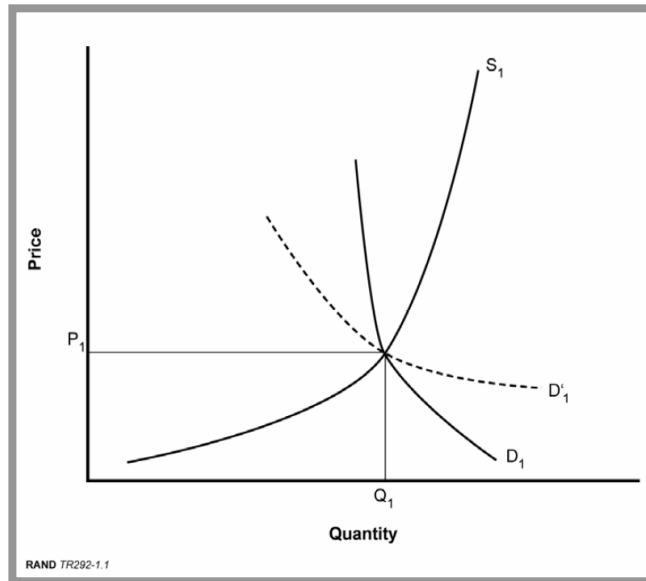
$$\text{Price elasticity of demand } (\eta) = \frac{\% \Delta \text{demand}}{\% \Delta \text{price}} \quad (2-1)$$

The two measurements of price elasticity of demand are: 1) own price elasticity of demand – the change in consumption within the same time period that the price change occurs, and 2) elasticity of substitution – the change in consumption across two time periods (such as peak and off-peak periods in TOU pricing), altering the relationship between these periods (King and Chatterjee, 2003).

Price elasticity estimates are typically in the ‘negative’ range conforming to economic theory, which states that as prices increase the demand for electricity will decrease. These estimates are generally combined with income elasticity of demand in econometric studies. Income elasticity of demand is defined as the change in demand for a commodity, such as electricity, when income increases or decreases. This has a ‘positive’ range indicating that as income levels increase, so too does the consumption of electricity as more household disposable income is available. Cross elasticity of demand is measured as the percentage change in demand for one commodity that occurs in response to a percentage change in price for another commodity. In terms of substitutes (such as peak and off-peak consumption) a 10% increase in peak prices, for example, will cause a 20% decrease in consumption giving a cross elasticity of 2.0 (Bernstein and Griffin, 2005)..

Figure 2-1 shows a conventional supply curve (S1) and two demand curves with different elasticities (D1 and D’1 respectively). Demand D1 is less elastic (i.e., ‘steeper’) than D’1. At equilibrium, both demand curves intersect the supply curve at the same point, with price at P1 and quantity at Q1 (Bernstein and Griffin, 2005).

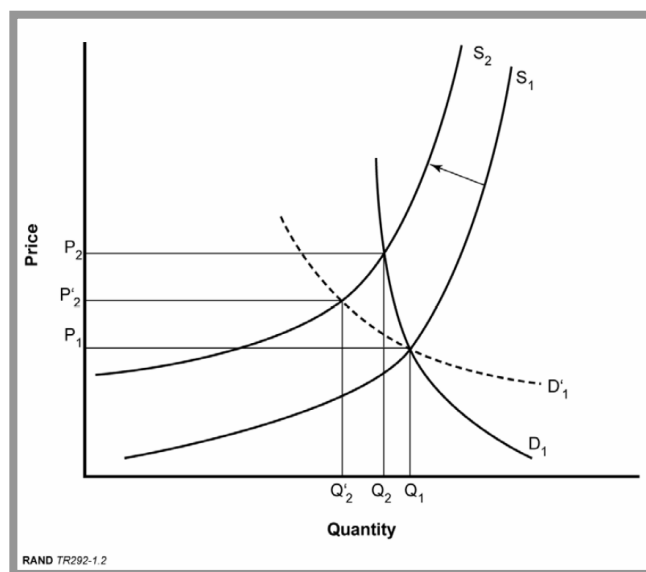
Figure 2-1: Relationship between supply and demand with two different demand curves



Source: Bernstein and Griffin (2005)

If the supply curve shifts inward (S_2) due to an increase in the cost of supply because of changes in primary fuel costs (natural gas for peaking plant, for example), the new equilibrium point would depend on which demand curve is used, as shown in Figure 2-2. If the demand is relatively inelastic (D_1) then prices will rise significantly with only a small reduction in demand. With the more elastic curve (D'_1) there is a larger reduction in quantity demanded for a smaller price differential.

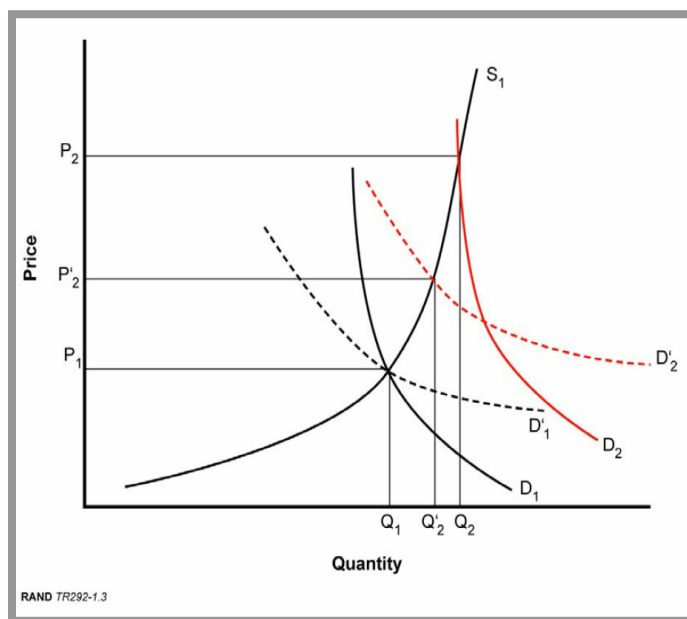
Figure 2-2: Impact of a shift in supply curves



Source: Bernstein and Griffin (2005)

If the demand for a commodity increases such that the demand curve shifts outward (D_1 to D_2), with no change in supply (S_1) then the more inelastic curve (D_2) sets a higher price at equilibrium (D_2, Q_2) than the more elastic curve (D_1, Q_1) as shown in Figure 2-3. Thus elasticity is a function of how consumers react to a change in price by reducing demand for a commodity.

Figure 2-3: Impact of a shift in demand curves



Source: Bernstein and Griffin (2005)

2.3 Price and income elasticity estimates for South Africa

Included in Whittaker and Barr (1989) is a critical assessment of the study done by Pouris in 1987 in which the author estimates a long-run '12-year' price elasticity of demand for SA of 0.90. The approach taken by Pouris (Whittaker and Barr, 1989) was to use electricity quantities sold (Gigawatt hours), electricity prices (cents (c)/kWh), consumer price index and 1975 gross domestic prices in a linear regression equation. Zarimba (2008) estimated a long-run price elasticity of demand of -0.011 and an income elasticity of 0.33 for SA. The variables included in this study were: 1) gross domestic product, 2) real per capita residential electricity consumption, and 3) the real residential electricity tariff (price). He concludes that residential demand for electricity in SA is both price- and income-inelastic and that a price increase alone will not discourage residential consumption. This study, however, is for the period 1987-2005 and does not include any of the recent (2009) tariff hikes proposed by Eskom.

2.4 Price and income elasticity estimates for other developing countries

A number of studies estimating the price elasticity of demand for residential customers were found in the literature. The following were selected and reviewed for this study:

- a) Ang et al. (1992) estimated the long-term income to be elastic at 1.0 and the price to be inelastic at -0.35 for Singapore from 1972 to 1990, despite the rapid growth in consumption over this period. They determined that the rapid growth was a result of the diffusion of household appliances, increases in the population as well as decreases in household sizes. They conclude that external influences in the form of energy efficiency campaigns were ineffective and the large variations in consumption between low- and high-income groups were primarily due to Heating, Ventilating and Air Conditioning (HVAC) units, leading to large seasonal variations in consumption.
- b) Filippini and Pachauri (2004) used disaggregated level survey data for 30 000 households in determining seasonal price and income elasticities for all urban areas in India. They show that the electricity demand was both price-inelastic (-0.42 for winter months, -0.29 for summer months and -0.51 for the monsoon period) and income-inelastic (0.60 to 0.64) for all three seasons studied. A great deal of heterogeneity in electricity demand was evident across individual households when disaggregated data was used. They also state that the regional variances in electricity consumed were significant and that the area of the household residence as well as its demographic (age of household head) had significant effects on consumption in urban India.
- c) Holtedahl and Joutz (2004) used aggregate data to examine the residential demand for electricity in Taiwan (1955 to 1996) as a function of disposable income, the growth in population, electricity prices and the degree of urbanisation. They found income to be unit-elastic in the long term (1.04) but inelastic in the short term (0.23). Price was inelastic at -0.15 – this low value was primarily due to low substitutes for heating and cooling in Taiwan as well as the fact that electricity is considered a basic commodity in the country. Using urbanisation as a proxy variable in their model they were able to capture economic development characteristics and changes in consumption not explained by ‘income’ itself. They conclude that urbanisation is a unique factor to consider for such studies in developing countries.

- d) Diabi (1998) also found the influence of urbanisation to have a greater effect than real income on the long- run price and income elasticities of demand estimates for Saudi Arabia (1980 to 1992). His estimates are both inelastic for price (-0.12) and for income (0.11). Data used in this study were average prices instead of marginal prices and aggregated consumption instead of individual consumption indicating that the estimates need to be interpreted as aggregated responses rather than responses by individual customers or households. The price of substitutes was excluded as a variable mainly because of very little inter-fuel competition in this country over the study period.
- e) Al-Faris (2002) studied the demand for electricity in the Gulf Cooperation Council countries (GCC). Despite four of the countries having the highest electricity consumption per capita in the world the study shows inelastic price and income elasticity estimates in the short-run. Short-run estimates for price average 0.09 and for income - 0.15, with the latter falling at the lower end of elasticities estimates for developing countries. This indicates that consumers in GCC countries consider electricity a necessity. Long-run estimates are higher, ranging from -1.10 for price and 0.33 for income (Kuwait) to -3.39 for price and 5.39 for income (Bahrain) indicating that price and income policies have a greater effect over time. In addition, consumers have greater flexibility in the long-run to curtail demand in response to higher tariffs.
- f) De Vita et al. (2006) estimated the long-run demand for energy using aggregated energy level data from the period 1980 to 2002 for Namibia. They found that both price (-0.30) and income (0.59) were inelastic for electricity and that consumers get 'locked' into a set of appliances for the provision of energy services they require and do not break away from their consumption patterns even though prices and incomes change, indicating again that electricity is considered an essential service.

2.5 Summary of international price and income elasticity estimates

A summary of some of the price and income elasticity studies is tabled in Appendix C. No significant pattern can be seen across developed or developing nations that indicates specific factors that contribute to price or income elasticities for electricity demand and most studies reveal consumers are inelastic to price changes and they tend to increase consumption when income levels rise. Long-run estimates are higher than short-run estimates due to consumers not being able to make short-term adjustments to appliance holdings (Reiss and White, 2005). These studies, however, take into account flat rate tariffs that do not differentiate

electricity purchase according to the time of day in which it is consumed, and thus provide little incentive to consumers to alter their consumption patterns accordingly (Langmore and Dufty, 2004). Furthermore, consumers in most countries consider electricity an essential service and do not reduce consumption upon price changes (examples include Holtedahl and Joutz, 2004; Al-Faris, 2002; De Vita et al., 2006).

2.6 Factors that influence residential customers price responsiveness

The factors that influence residential customers' electricity consumption patterns and the ability of households to respond to price changes are described below. These factors are listed with reference to a number of econometric studies done as to how these factors affect consumer responses to time-varying rates.

2.6.1 Appliance ownership

The consumption of electricity of a household is dependant on the energy-using appliances within that household (Reiss and White, 2005). Households at higher levels of use show greater price elasticities mainly because of their greater levels of appliance ownership. The possession of air conditioning, electric space heating, water heating, clothes dryers and swimming pools all increase price elasticities notably (Acton and Park, 1984).

Appliance ownership strongly influences the estimates of price elasticities and customer responses to TOU pricing (Acton and Park, 1984; Faruqui and Malko, 1983; Caves et al., 1984a, Hausman and Trimble, 1984; Baladi et al., 1998). This is an important aspect in studying the effects of TOU pricing in terms of short- and long-term elasticity estimates. In the short term, changes in household income as well as changes in electricity prices affect consumption due to the intensity of use of current appliances (e.g., changing the thermostat level of an air-conditioner). In the long term households may adjust their appliance types (purchasing newer types of appliances), mainly due to changes in income (Garbacz, 1983). Appliances that are weather related, such as electric space heating for example, have a relatively low capital cost but a high operating cost and are, therefore, more likely to be used on an incidental basis rather than a sustained basis in cold climate areas or during winter periods (Houthakker, 1980). Discretionary use (e.g., electric kettles and pool pumps) as opposed to essential use of appliances (e.g., refrigeration and space heating) strongly influences how customers alter their electricity consumption patterns when faced with TOU rates (Filippini, 1995).

Reiss and White (2005) modelled end use electricity demand using eight appliance categories: 1) a baseline; 2) electric space heating; 3) central HVAC; 4) room HVAC; 5) electric water heating (Hot Water Convertors (HWCs)); 6) swimming pool pumps; 7) additional refrigerators and freezers; and 8) other appliances. The baseline category accounted for consumption by universally-owned appliances such as lighting loads, the primary (first) refrigerator or freezer and included ‘unspecified’ appliances such as electric clocks, irons, hair dryers, etc. This was then compared to categories 2 to 6 – energy-intensive appliances whose utilisation exhibited significant price elasticities (Electric Power Research Institute, 1989). Reiss and White state that the estimated price effects varied substantially across appliances with the baseline use effectively zero whilst all other appliances exhibited significant price sensitivity as indicated in Table 2-1.

Table 2-1: Estimated marginal effects of appliances on consumption

Effect on consumption per month (kWh) ¹						
Variable	Baseline	Electric space heating	Central HVAC	Room HVAC	Electric water heating	Swimming pool
Price (c/kWh)	0.4	-37.8	-22.5	-63.4	-34.0	-27.5
Income ('000 \$)	0.4	16.2	9.1	21.6	32.8	6.3
No. of occupants	18.0	-7.9	-38.6	-52.1	47.5	-
No. of rooms	12.9	20.4	9.8	29.2	-35.3	-
No. of bathrooms	27.0	-	-	-	-	-
Heating degree days	-10.6	43.3	-	-	-	-
Cooling degree days	-59.5	-	233	45.1	-	-

¹ Marginal effects shown were estimated on population mean and are conditional on appliance ownership

Source: Reiss and White (2005)

These estimates are of practical significance, for example:

- a) A marginal increase in electricity price (1c/kWh) would result in a decrease in consumption of 37.8 kWh per month (453.6 kWh per year) in electric space heating and 34 kWh decrease in consumption (408kWh per year) in electric water heating,
- b) A marginal increase in income would result in an increase of 32.8 kWh per month (393.6 kWh per year) in electric water heating,
- c) The utilisation of temperature-sensitive appliances increases depending on the number of heating degree days (HDD) (43.3 kWh per month for electric heating) and is significantly higher for cooling degree days (CDD) (233 kWh per month for HVACs).

In their study of the short- and long-term electricity demand for residential customers in the Gulf-state Utilities Company, Kahn et al. (1986) incorporated appliance capacity and efficiency ratings in their study rather than appliance ownership levels alone. By incorporating these engineering parameters into their estimations, they were able to account for the short- and long-term effect on electricity demand response to price changes as separate components of utilisation and appliance adjustments, respectively. In the short-term appliance ownership is assumed to be fixed and the only response to changes in electricity price is customer behaviour (Kahn et al., 1986).

2.6.2 Household demographics

In 2001, 91.8% of employed men and 86.3% of employed women worked on a full time basis in SA (Statistics South Africa, 2001). This indicates that 9 out of 10 working adults would not be at home during typical morning peak periods (07h00 to 10h00) but are more likely to be at home during evening peak periods (18h00 to 20h00). The largest age category for the SA population was the 10-14 year old (11.3%) followed by the 5-9 year old category (10.8%), indicating a high proportion of young children and teenagers in the population as a whole. Pensioners in the 55 years old and above category (female pension able age) made up 2.8% of the population whilst pensioners in the 65 years old and above category (male pension able age) made up 1.6% (Statistics South Africa, 2001).

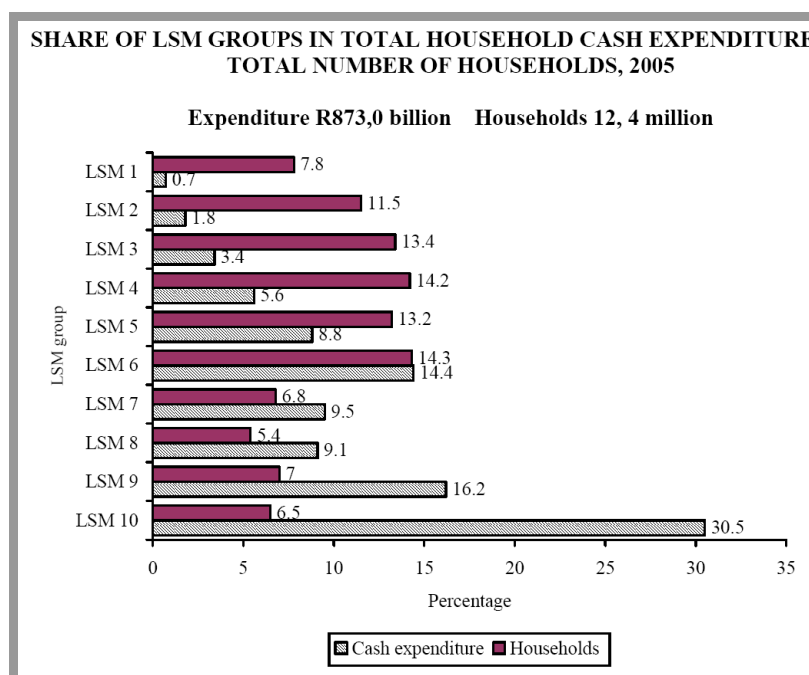
2.6.3 Income

The income of the employed in SA is relatively low. 1996 census data showed that 3.9 million employed people earned 1 000 Rand (R) or less after tax per month, a further 3.9 million employed earned between R1 001 and R4 500, 775 800 between R4 501 and

R11 000 whilst as few 166 000 earned more than R11 001 per month (Statistics South Africa, 2001). The 2001 data showed that 3.2 million employed people earned R800 or less per month before tax, 3.9 million earned between R801 and R3 200, 2 million between R3 201 and R12 800 and as few as 439 800 earned an income of R12 801 per month after tax (Statistics South Africa, 2001).

The expenditure on housing and electricity as a source of energy varies across different Living Standards Measure (LSM) groups with LSM 1-4 spending 8.4%, LSM 5-7 spending 36.8% and LSM 8-10 spending 54.8% of total household cash expenditure on housing and electricity. LSM 6 in particular, which comprises the largest portion of the number of households in SA, spends 17.28% of household expenditure on housing and electricity compared to the impoverished end of the spectrum LSM 1 (4.37%) and that of the wealthier class LSM 10 (13.63%) (Martins, 2006).

Figure 2-4: SA household expenditure and total number of households in 2005



Source: Martins (2006)

2.6.4 Alternative energy sources

In 1996 the proportion of SA households using electricity for cooking was 46.9% and this increased to 51.4% in 2001. Dependence on other energy sources, such as gas, paraffin, wood and coal, for this function decreased. Electricity used for heating increased from 44% in 1996 to 49% in 2001. The largest increase was that of lighting which increased by 12.4%

from 1996 (57.3%) to 2001 (69.7%) with less dependence on paraffin for this function (Statistics South Africa, 2001).

2.6.5 Climatic conditions

Electricity consumption by space and water heating is strongly influenced by variations in temperature and climatic conditions and is accounted for in econometric studies by the number of HDD and CDD in a year. These are determined using the differences between daily ambient and ‘base’ temperatures and are a measure against which changes in electricity consumption are recorded. The energy used for water heating, for example, depends, in part, on the intake temperature of the water and is thus a function of outside temperature. The consumption by refrigerators on the other hand depends on the inside temperature and is thus a function of ambient conditions inside the home (Houthakker, 1980).

The calculation of ‘heating degree hours’ (HDH) and ‘cooling degree hours’ is more specific to the analysis of TOU pricing and is a measure of the difference in hourly ambient temperatures and a ‘base’ temperature. The difference between the average peak HDH in a day and the average off-peak HDH gives the average daily HDH (Faruqui and Sergici, 2009).

2.6.6 Tariff design

The design of TOU tariffs which include the range of peak to off-peak price ratios, length of the on peak period and whether rates are revenue neutral, i.e., designed to leave total revenue unchanged under zero elasticity, has important implications for experimental results as well as policy applications (Faruqui and Malko, 1983). When the ratio of peak to off-peak is set too low, very little shifting of use occurs, as happened with the Idaho Power residential pilot programme of 2005 and 2006 (Faruqui and Sergici, 2009). The greatest benefit from TOU pricing is achieved when the peak to off-peak price ratio is equal to the peak to off-peak price ratio of marginal costs of supply. If poorly designed, TOU rates may provide a worse approximation of marginal costs than existing flat rate tariffs (Faruqui and Sergici, 2009).

Caves et al. (1984b) state that the price differential between peak and off-peak consumption is the primary factor that determines the extent of customer response to TOU pricing. They indicate discernible effects of appliance holdings, customer characteristics and the climate variations on customer response but that these are not as strong as the effect of the price differential.

2.7 The current residential electricity tariffs in South Africa

“To ensure greater economic efficiency and welfare in the electricity industry, tariffs and their pricing signals must reflect the economic value of the service provided, while considering how the resources providing this service are equitably allocated within the community. In order to achieve economic efficiency, prices and tariff structures should be based on current cost drivers, but must consider the sustainability of the business by taking into account long-range marginal costs. Tariffs, in both structure and level need to minimise the risk to the business and consider the customer’s ability to respond to any pricing signals. Tariff structures should contain pricing signals that persuade customers to optimise their use of Eskom’s resources as much as possible. In the current environment of no surplus generating capacity and network constraints, economic efficiency is of particular importance as a pricing strategy. Tariffs now, more than ever, need to ensure that the correct signals are sent to customers reflecting the cost of energy and capacity on a daily basis” (Eskom, 2007).

The general mathematical formula for determining rate levels for monopoly services begins with a computation of total revenues (revenue requirement) necessary to meet demand for service, as follows:

$$RR = E + d + T + [r * (V - D)] \quad (2-2)$$

where:

RR = Revenue requirement, or total revenues

E = Expenses

d = Annual depreciation expense

T = Taxes

r = Weighted average cost of capital

V = Original book value of plant in service

D = Accumulated depreciation

Note: (V - D) = ‘Net rate base’

The period under examination is called the ‘test year’. In many places, rates are set using an historic test year, adjusted for known and measurable changes. The exercise yields an adjusted test year cost of service that is meant to be a predictor of a company's revenue needs during the period rates will be in effect. The simplest way to set rates would be to divide the revenue requirement by sales volume (kWh), as follows:

$$\text{Rates} = \text{RR}/\text{Volume of sales} \quad (2-3)$$

Although actual rate setting is somewhat more complicated than this (for example, customers are grouped according to their use patterns, and the revenue requirement is allocated among those classes according to principles of cost causation), but the essential mathematical relationship holds in that the product of rates and sales is the general revenue requirement for a utility.

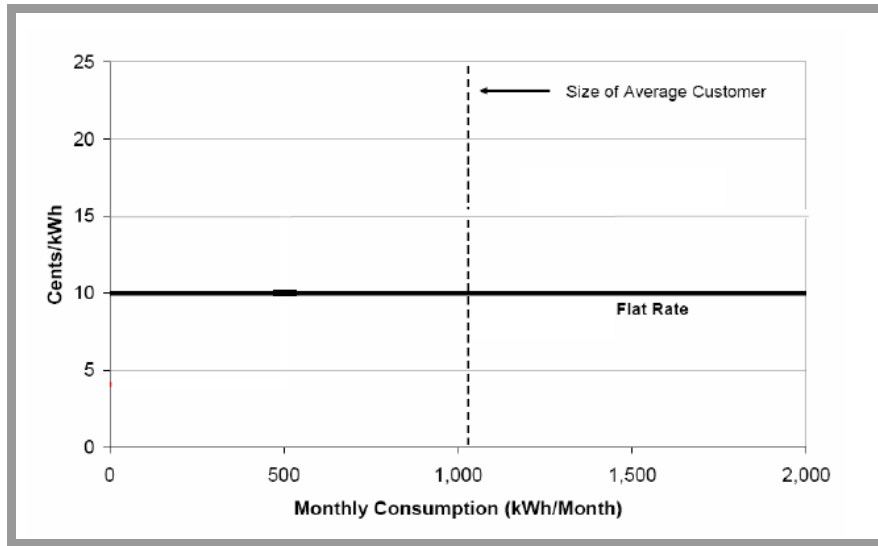
2.7.1 Flat rate tariffs

The most common retail electricity pricing practice all over the world, before deregulation and even after deregulation, is the flat rate tariff or fixed pricing per kWh of energy consumed (Celebi, 2005). Under this structure households are subject to fixed access charges and a constant rate for marginal consumption, and thus face the same purchasing decisions throughout the day, irrespective of the time of use. Low income is associated with lower average consumption and these households are disadvantaged by the way standing charges raise the average unit costs. Efforts to induce reduction in consumption fail in this low-LSM sector since these households perceive reduction efforts as providing little difference in overall bill size (Langmore and Dufty, 2004).

The burden placed on system capacity by some customers is greater than that which is reflected by their energy consumption levels. This is due to intense use of appliances such as air conditioners, dishwashers or clothes dryers during peak periods. The implication of this is that some customers who consume only small quantities during peak times actually cross-subsidise those creating disproportionately higher peak period demand. Average prices also create efficiency problems associated with over consumption of capacity during peak times and under consumption during off-peak times (Langmore and Dufty, 2004).

A flat rate tariff not only presents the customer with a peak to off-peak price ration of unity but also with the freedom to arbitrarily select the timing of use of electrical appliances without regard to cost (Caves et al., 1984a).

Figure 2-5: Illustration of a flat rate tariff

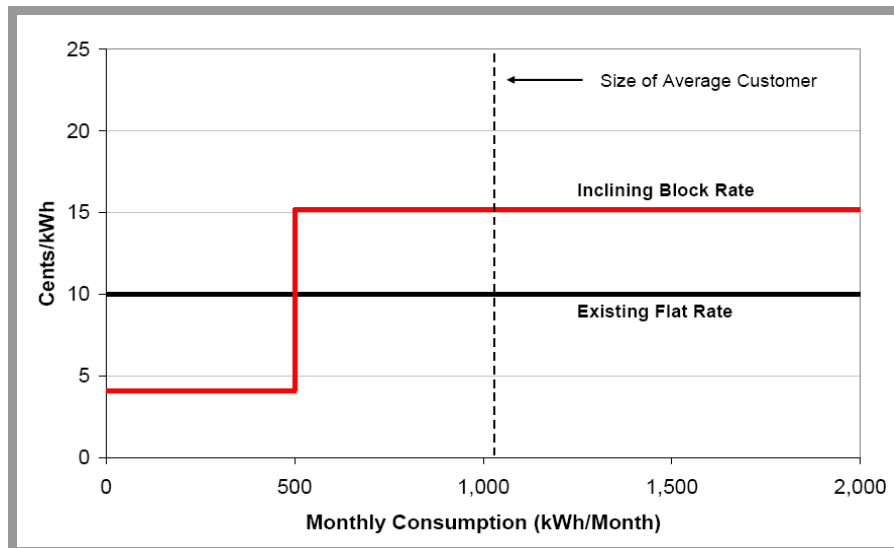


Source: Faruqi and Wood (2008)

2.7.2 Inclining block tariffs

These tariffs incorporate a fixed charge, an initial energy cost at a low marginal rate and subsequent higher cost at higher consumption levels, e.g., 4c/kWh from 0 to 500kWh and 15c/kWh for all consumption in excess of 500kWh, this example is illustrated in Figure 2-6.

Figure 2-6: Illustration of an inclining block tariff



Source: Faruqi and Wood (2008)

Inclining block tariffs raise the cost of marginal consumption for higher volume customers and are able to provide an incentive for reduction in marginal consumption. Given the

relatively low price elasticity for SA (-0.011) as estimated by Zarimba (2008), the long-run responsiveness of high consumption customers to these price signals may be limited. The advantage of inclining block tariffs is that they provide lower marginal prices to those who consume less and since lower incomes are associated with lower average consumption, these customers will benefit.

The disadvantage of these schemes is that they do not target peak reductions because they send out a broad signal for high volume customers as opposed to tariffs that differentiate between peak and off-peak pricing. The incentive to substitute consumption between peak and off-peak periods may be negated by inclining block tariffs since prices are increased for high consumption customers irrespective of the TOU. This also leads to cross-subsidisation of small and large customers who use intensively in peak periods (Langmore and Dufty, 2004).

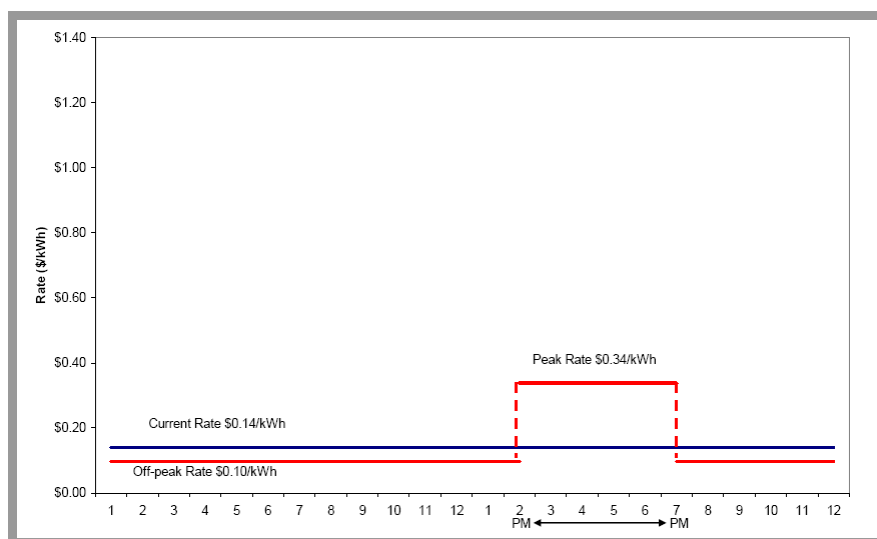
2.7.3 TOU tariffs

The problem with flat rate and inclining block tariffs is that customer demand is artificially inelastic because customers face only averaged prices, which are limited in their ability to reflect costs associated with underlying system capacity. A primary reason as to why these tariffs continue to be the convention is the existing metering technology installed for the mass market. Basic electromechanical meters are used that measure only aggregated consumption and these are read monthly, quarterly or yearly. These lagged billing cycles further exacerbate the problem since the consequences of consumption decisions are felt months after they made and thus provide poor feedback mechanisms to consumers. Basic metering and lagged billing cycles impose limitations upon conscious consumer decisions as well as cost reflective price structures (Langmore and Dufty, 2004).

TOU rates, which charge different prices for electricity consumption depending on the time at which electricity is used, have been proposed as an alternative to traditional time-invariant rate structures for two main reasons: 1) they more accurately reflect the time-varying costs associated with electricity supply and can be expected to improve the efficiency of resource allocations, and 2) they provide an incentive to customers to modify their use patterns by reducing peak loads and shifting use from peak to off-peak periods. Thus, by reducing reliance on peaking plant TOU rates can be expected to slow the trend of rising electricity prices (Faruqui and Malko, 1983).

An example of a TOU tariff is illustrated in Figure 2-7. The off-peak rate of US Dollar (\$) 0.10/kWh is lower than the flat rate of \$0.14/kWh providing an incentive for customers to consume during these periods. The peak rate of \$0.34/kWh is higher than both the flat rate and off-peak rate and is generally aligned to system peak hours when supply costs are higher. The peak to off-peak price ratio is roughly 3:1.

Figure 2-7: Illustration of a TOU tariff



Source: Faruqi and Wood (2008)

TOU pricing allows for variations in the price of electricity across time of day, day of month, month of year and season of year. Price levels are preset for predetermined hourly and daily intervals to reflect prices under expected *long-term* conditions. The advantage of TOU pricing is that it provides incentives to customers to load shift whilst securing price predictability for the utility. The limitation of TOU is that although it may capture trends such as morning and evening peaks, its prices cannot reflect unpredictable load variability that may arise and thus affect electricity supply costs in real time (Langmore and Dufty, 2004).

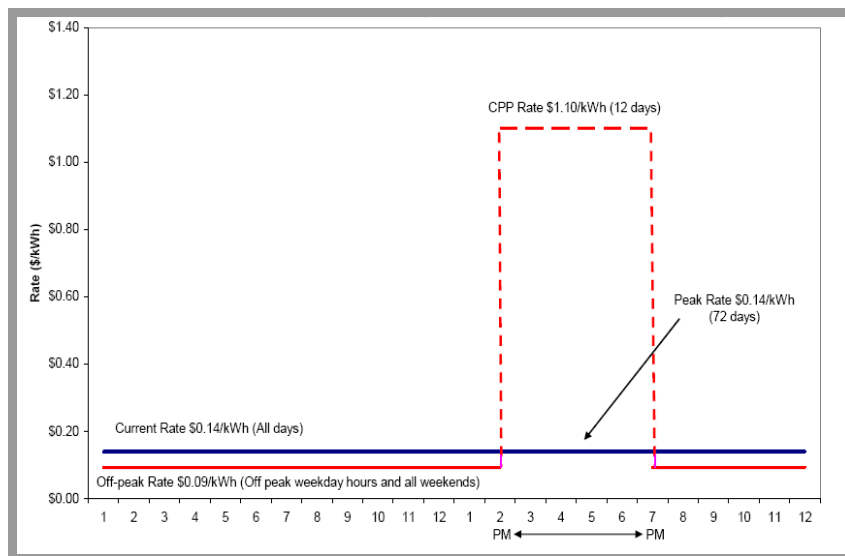
In order to implement TOU tariffs, specialised interval metering (referred to as ‘smart meters’) is required to be installed at each customer supply point, replacing the existing conventional type meters. Smart meters also require some form of communication to retrieve the interval data. A cost benefit analysis is then required in order to substantiate the benefits from TOU pricing against the substantial increase in metering costs required to implement such tariffs (Caves et al., 1984b)

Several studies that explored the effect of TOU rates on customer behaviour when exposed to this tariff have found that these rate structures have been effective in reducing peak period consumption (examples are to be found in: Taylor and Schwarz, 1990; Aigner and Lillard, 1984; Baladi et al., 1998; Caves et al., 1987; Filippini, 1995; and Faruqui and Malko, 1983). A detailed review of some of the utilities that have experimented or implemented TOU pricing is to be found in Section 2.9 of this chapter.

2.7.4 Critical peak pricing

Critical peak pricing (CPP) is a form of dynamic pricing that improves upon traditional TOU rates by allowing prices to reflect the underlying uncertainty in supply costs. This allows prices to more closely reflect changes in wholesale prices (Faruqui and Wood, 2008).

Figure 2-8: Illustration of a CPP tariff



Source: Faruqui and Wood (2008)

2.8 Price elasticity studies specific to time-varying pricing tariffs

The following section briefly reviews some of the studies that specifically involve time-varying tariffs by analysing the factors that contribute to the price elasticity estimates due to customers' responses to these rates. Of interest in these studies are 'elasticities of substitution' estimates, which identify the substitution of electricity consumption across the different time-varying rates.

2.8.1 The elasticity of substitution

The elasticity of substitution was designed as measure of the “ease of which the varying factor can be substituted for others” (Samuelson, 2001). This is a function of the cross-elasticity of demand, which measures the responsiveness of the quantity demanded of a commodity to a change in the price of another commodity. This is often considered when looking at the relative changes in demand when studying complement and substitute goods. Complement goods are goods that are typically utilized together and if one is consumed, usually the other is also. Substitute goods are those where one can be substituted for the other. If the price of the one commodity rises, a consumer may purchase less of it and instead purchase its substitute. Examples of substitutes are margarine for butter and natural gas for electricity in terms of space heating (Wikipedia, 2009a).

In terms of TOU electricity pricing, the ‘goods’ are peak and off-peak consumption. When a customer is faced with a higher peak period price, he/she may substitute peak period consumption for off-peak period consumption by switching off certain appliances during the higher priced peak periods and back on during the lower priced off-peak periods.

The Constant Elasticity of Substitution (CES), in economic terms, is an aggregator function that combines two or more types of utility consumption. There is a constant percentage change in factor (e.g., peak and off-peak period prices) proportions due to a percentage change in the marginal rate of technical substitution (e.g., peak and off-peak period consumption) (Wikipedia, 2009b).

2.8.2 Factors that affect customer response to TOU pricing

The following factors that account for the response of customers to TOU pricing have been identified in the literature. A brief overview of each factor is given as follows:

2.8.2.1 Appliance ownership

Caves et al. (1984a) used data from five experimental TOU rates in the US including 9 000 customer observations and accounting explicitly for appliance ownership, housing characteristics and climatic conditions. Their estimates show that the substitution elasticity is greater for customers who own more appliances (0.21 for a customer with all major appliances) than those who did not own any major appliances (0.07 for a customer with no

major appliances). Space cooling appliances such as air conditioners increase the elasticity estimates from 0.11 (customer with no HVAC) to 0.16 (customer with HVAC) indicating the interaction between appliance ownership and climate.

Baladi et al. (1998) found similar results for the Midwest Power experiment of the 1990s in which 2 400 volunteer residential customers were placed on TOU rates. They state that a household with none of the major appliances has a smaller elasticity of substitution estimate (-0.006) between peak and off-peak use when compared with an 'all electric home' (0.39). They conclude that households with major appliances have a greater ability to shift use across time varying rates.

Faruqui and Malko (1983) surveyed 12 experiments with TOU pricing in the US from 1975 to 1981. They also found that the peak period own price elasticity increases with the ownership of major appliances for the Wisconsin experiment. The variations in price elasticities of peak and off-peak consumption range from nil to -0.4 across the experiments and this variation is due to, amongst others, the appliance ownership levels of the customers in the experiment samples. The authors conclude that the long-term impact of TOU rates on customer response must include an assessment of the changes made to appliances owned.

Hausman and Trimble (1984) argue that almost all electricity use takes place in conjunction with durable appliance use and thus a short-term experiment is unlikely to induce a significant change in households' durable holdings. They analysed the Central Vermont Public Services voluntary time of day (TOD) rates, which were offered to customers from 1976. They found a significant response to TOD rates through appliance purchases and that these have an effect on off-peak and peak use shares as well as total consumption.

In his study of 220 households across 19 Swiss cities, Filippini (1995) included electrical appliances as an exogenous household characteristic in an ideal system demand model. The results show that the demand for peak (-1.25 to -1.41) and off-peak (-2.30 to -2.57) consumption is elastic. The cross price for peak to off-peak is positive (0.34 to 0.41) as well as off-peak to peak (0.97 to 1.57). He concludes that peak and off-peak consumption are substitutes in the Hicks-Allen sense and obtains an elasticity of substitution between 2.56 and 2.98 for the Swiss study.

2.8.2.2 Climatic conditions

Caves et al. (1984a) studied five experimental residential TOU rates in the US during the 1970s and found an interaction between appliance ownership and climatic effects. In addition they found that climate effects are larger in the presence of full appliance ownership and in warm climates. This is due to the intense use of HVACs (air conditioners) in the US during warm periods. Aigner and Lillard (1984), Houthakker (1980) and Kahn et al. (1986), also found that climatic conditions affect customer responses to time-varying rates when weather sensitive appliances are explicitly accounted for.

2.8.2.3 Household characteristics

In a study of the effects of peak and off-peak electricity consumption of 220 Swiss households, Filippini (1995) found that the size of the residence as well as the presence of children strongly influences the elasticity estimates. Additionally, discretionary use of water heaters strongly influences electricity consumption. Estimates for partial cross-price elasticities are between -1.25 and -1.41 for peak periods and -2.30 and -2.57 for off-peak periods. Elasticity of substitution estimates lie between 2.56 and 2.98. The positive elasticity of substitution estimates indicate that off-peak and peak electricity consumption are substitutes (Samuelson, 2001). The study was based on the assumption that electricity was separable from other goods, holding total expenditure constant and conditional upon allocation of total expenditure between electricity and other goods (Filippini, 1995).

Caves et al. (1984a) found that an increase in the number of residential occupants decreases the elasticity of substitution. They state that mobile home dwellers shift more of their consumption than do single family detached houses, and apartment dwellers exhibit the least shift in consumption. The authors do indicate, however, that these effects were not measured precisely. Lawrence and Braithwaite (1979), however, state that the social demographics of the occupants, in particular the adults, as well as the number of children living in the household, play a more significant role than the size of the residence (Filippini, 1995; Langmore and Dufty, 2004).

The number of adults at home during the day is a factor in overall consumption but this also facilitates load shifting from off-peak to peak periods (morning peaks). The effect of both parents working plays an insignificant role in changing consumption patterns. The ages of children are also a factor since older children, typically teenagers, tend to utilise appliances

more than younger children (Langmore and Dufty, 2004). Households where at least one member is retired, or that have a housewife, are expected to consume more electricity during peak periods than households with only workers (Filippini, 1995).

2.8.2.4 Income

Reiss and White (2005) found statistically insignificant income elasticities when household appliance ownership was explicitly accounted for in their model. This is due to the effect of income on consumption through the household's choices of appliances rather than utilisation behavioural changes. These low estimates of appliance utilisation income elasticities are consistent with previous studies (e.g., Reiss and White, 2005). However, when estimating price elasticities by income level alone, they found that as household income increases, price elasticity estimates decrease. This indicates that households with lower income levels are more sensitive to energy price increases. They show estimates based on annual income of -0.49 (less than \$18 000), -0.34 (\$18 000 to \$37 000), -0.37 (\$37 000 to \$60 000) and -0.29 (more than \$60 000). Thus when faced with a 1% increase in price due to a TOU tariff, customers earning less than \$18 000 will reduce consumption by 0.49% whilst customers earning more than \$60 000 will only reduce by 0.29%.

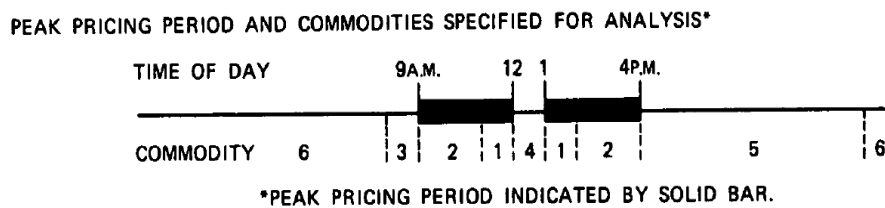
2.8.2.5 Total consumption

In determining how price elasticities vary with the level of consumption, Reiss and White (2005) found that as consumption increases, the price elasticity estimates decrease. This despite the fact that higher consuming households possess energy-intensive appliances that, all else being equal, have greater price sensitivity. They explain that this inverse relationship between income and consumption (energy-intensive appliance ownership) is due to the fact that households are price inelastic as income level increases. Estimates for price elasticities by household annual consumption are +0.37 (less than 4 450 kWh), +0.04 (4 450 kWh to 6 580 kWh), -0.00 (6 580 kWh to 9 700 kWh) and -0.08 (more than 9 700 kWh per year) when the Ordinary Least Squares (OLS) method was used. This indicates that the effect of raising revenue purely based on consumption will be minimised if marginal price changes are disproportionately larger for high consuming customers.

2.8.2.6 Tariff design

The Wisconsin TOU experiment conducted during 1976 to 1980 was used to determine the responsiveness of residential customers to TOU rates. The price ratio of peak to off-peak periods was multiples of 8,4,2 and 1, where 1:1 served as the control group. The system peaks occurred during the summer months (July and August) for the Wisconsin Public Services Corporation and these were of particular interest in determining the effect of TOU pricing on customer preferences in: 1) reducing consumption in critical hours within the peak periods of the tariff, and 2) if any consumption outside the periods was significant enough to cause ‘needle peaks’ (Caves et al., 1987). The authors approached these questions by allocating the consumption by TOU customers to six distinct commodities even though there were only two unique prices. Commodity 1 was allocated to the system peak hours within the peak periods, commodity 2 to the remaining hours in the peak periods and commodities 3, 4 and 5 to hours adjacent to peak periods. Commodity 6 was then allocated to the remaining hours (Caves et al., 1987).

Figure 2-9: Peak period pricing and commodities specified for analysis



Source: Caves et al. (1987)

Caves et al. (1987) analysed the pattern of substitution across the sub periods and show six elasticity of substitution estimates. They state that the elasticity of substitution during the critical hours is larger than that during the remaining peak hours, implying that customers reduce consumption during these hours ($\sigma_{10}^e > \sigma_{20}^e$). Off-peak substitution elasticity estimates are greater in overnight off-peak periods than daytime off-peak periods ($\sigma_{6p}^e > \sigma_{3p}^e, \sigma_{4p}^e, \sigma_{5p}^e$) indicating that no significant ‘needle peak’ occurs at hours adjacent to peak periods (Caves et al., 1987).

Taylor and Schwarz (1990) analysed the long-term effects of TOU rates by using data from the Duke Power non-experimental TOU tariff from 1995 to 1998, particularly the summer months of June to August. This tariff consisted of a maximum demand charge (kW) as well

as consumption charges (off-peak and peak kWh). Demand charges were included in the tariff so as to price capacity and energy separately in order to prevent ‘needle peaks’ in demand. The authors included ‘customer experience’ as a factor in the long-run effects of TOU pricing and found that the longer customers are exposed to such tariffs the more own price elasticity of demand estimates increase in the long run (from -0.375 to -0.392, 0 to 10 years homothetic experience, respectively, and -0.400 to -0.415, 0 to 10 years non-homothetic experience, respectively, for a typical summer month). Cross price elasticity of peak energy also increases with respect to the demand charge (from -0.832 to -0.991, 0 to 10 years homothetic experience, respectively, and from -0.821 to -1.090, 0 to 10 years non-homothetic experience, respectively). The elasticity of substitution between off-peak and peak energy also increases in absolute value over time (from -0.569 to -0.683, 0 to 10 years, respectively, and -1.240 to -1.480, 0 to 10 years, respectively, for a typical summer month). Thus, the demand charge induces a greater reduction in peak energy consumption and has a greater *indirect* effect in the long run.

2.8.2.7 Participation level

Residential customer participation in TOU programmes is normally done on a volunteer basis. A concern with voluntary programmes is that volunteers may consist mainly of those customers who already use little to no electricity in high priced periods and thus have limited ability to shift use. The effect of this is that revenue losses to the utility are shifted to non-volunteers in the form of general tariff increases (Baladi et al., 1998).

In analysing the self-selection bias from the Los Angeles experiment in the 1970s, Aigner and Ghali (1989) found an over estimation of the elasticity of substitution of 0.177 and corrected this, by adapting a well-used econometric methodology, to 0.094. The bias was as high as 24% averaged across the seven sub-experiments within LA. They warn that volunteer customers bias the results of TOU experiments resulting in a substantial overstatement of response in such programmes. This is of particular importance if inferences are to be made to inform future mandatory implementation of TOU pricing.

The demand responses estimated under TOU pricing have often been obtained under ‘experimental’ conditions. In turn, this may have created heightened awareness of consumption and pricing, facilitating larger demand responses than might otherwise have occurred under ‘normal’ conditions. The behavioural differences resulting from experimental participation (otherwise known as the Hawthorne effect) mean that where the informational

effects from the experiment are not accounted for, the influence of price signals upon demand may have been overstated (Langmore and Dufty, 2004; and Taylor and Schwarz, 1990).

2.8.2.8 Enabling technology

Faruqui and Sergici (2009) surveyed 15 of the most recent experiments with dynamic pricing and found that technology has an impact on elasticity estimates as well as customer responses to these tariffs. Utilities that have installed enabling technologies (Public Service Electric and Gas Company, New Jersey, and Gulf Power) to assist customers to respond to TOU tariffs have found a greater response than utilities without these technologies (Ontario and Puget Sound Energy). A full review of these is to be found in section 2.9 of this Chapter.

In investigating the effects of TOD electricity pricing for the Central Vermont Public Service Corporation, Hausman and Trimble (1984) found that 60% of customers in the TOD sample purchased timing devices to control hot water use whilst 50% purchased timing devices to control heating appliances. Furthermore they state that these devices have a significant impact on the share of both peak and off-peak as well as total consumption.

2.9 International experiences with experimental residential tariffs

Faruqui and Sergici (2009) surveyed the experimental evidence from some of the dynamic pricing programmes made available to customers in some US states as well as other countries. The following is directly referenced from the author's summary of these programmes:

2.9.1 Anaheim Public Utilities – California

A dynamic pricing programme was conducted between June 2005 and October 2005 in which 123 customers participated: 52 control customers and 71 treatment customers. The programme did not provide a critical peak rate to customers but rather a rebate of \$0.35/kWh for reduction during critical times. No self-selection bias was evident. The data showed that the treatment group used 12% less on average during the peak hours compared to the control group and response was greater on higher temperature days.

2.9.2 Automated Demand Response System Pilot – California

This experiment was conducted from 2004 to 2005 and operated under a CPP tariff. The tariff was supported with residential-scale automated demand response technology and allowed users to install an advanced home climate control system (GoodWatts). Users were able to program their preferences for the control of appliances. Peak periods were from 14h00 to 19h00 with all other hours (including weekends and holidays) subject to a base rate. The ‘super peak’ price ratio was 3:1 to peak. Peak reductions by programme participants were 51% on event days and 32% on non-event days with enabling technologies emerging as the main driver, especially for super peak events and for high consumption customers.

2.9.3 State-wide Pricing Pilot – California

This programme was conducted across three of California’s investor-owned utilities – Pacific Gas & Electric (PG&E), Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E) – from July 2003 to December 2004 to test the impact of several time-varying rates:

- a) TOU where the peak to off-peak price ration was 2:1.
- b) CPP where the peak price to off-peak price was roughly 5:1 during critical days and on non-critical days the TOU rate was applicable. The two variations of the CPP were:
 - CPP-F rate – a fixed period of critical peak and day-ahead notification with no enabling technology available. Average peak price was \$0.59/kWh on critical days, \$0.22/kWh on non-critical days and the average off-peak price (\$0.09/kWh) was lower than the standard rate (\$0.13/kWh).
 - CPP-V – a variable length of critical peak and notification time with customers given the choice of enabling technology. Average peak price was \$0.65/kWh on critical days and the average off-peak price (\$0.10/kWh) was lower than the standard rate (\$0.14/kWh). This rate schedule was tested on two treatment groups: 1) Track A – customers who consumed more than 600kWh per month and had higher income levels and HVAC ownership than the average population with two-thirds opting to have enabling technologies installed, and 2) Track C – customers who previously had volunteered for a smart thermostat pilot and thus already had enabling technologies installed.

TOU customers reduced consumption by 5.9% in 2003 but small sample problems meant a proper estimation of the impacts could not be provided. CPP-F customers reduced consumption by 13.1% on critical days. CPP-V Track A customers reduced consumption by 16% and Track C customers by 25%. The impact from CPP-V (Track A & C) customers was larger than that of CPP-F customers – this suggests that the response was larger for customers with enabling technologies than without.

2.9.4 XCEL Energy TOU Pilot – Colorado

This was a pilot programme that tested the impact of TOU, as well as CPP, from 2006 to 2007 and consisted of 2 900 volunteer customers as a final sample. The programme used an automatic meter reading system with all customers having interval metering and some customers offered enabling technologies such as HVAC switches and programmable thermostats. The rates options were TOU, CPP and CTOU (critical peak and TOU). Demand response was -5.9% for TOU, -44.81% for CPP and -46.86% for CTOU, both with enabling technology. However, self-selection bias may have played a role in the impact results.

2.9.5 Gulf Power Select Programme – Florida

Gulf Power ran a programme starting in 2000 that provided customers with three different service options:

- a) A standard rate (RS) option with a flat rate of \$0.057/kWh applicable at all hours.
- b) A conventional TOU (RST) option with an off-peak rate of \$0.027/kWh (00h00 to 12h00 and 21h00 to 00h00) and a peak rate of \$0.104/kWh (12h00 to 21h00)
- c) A three-period CPP (RSVP) with an off-peak rate of \$0.035/kWh (00h00 to 06h00 and 23h00 to 00h00), mid-peak rate of \$0.046/kWh (06h00 to 11h00 and 20h00 to 23h00), peak rate of \$0.093/kWh (11h00 to 20h00) and a CPP rate of \$0.29/kWh applicable when called by the utility.

The customers under the CPP schedule showed a 2.1kWh (per household) demand reduction during peak and 2.75kWh during critical peak. This amounted to a 22% energy reduction during peak and 41% reduction during critical peak when measured against the 6.1kWh baseline.

2.9.6 Électricité de France – France

Électricité de France (EDF) – the French utility – initiated the Tempo programme in 1996 which consisted of a peak period (06h00 to 22h00) and an off-peak period (22h00 to 06h00). A distinct feature of the programme was the day-of-year pricing schedule, which grouped the 365 days into:

- a) 300 Blue days, which made up the least expensive days (Euro (€) 0.0464 for off-peak and €0.0577 for peak).
- b) 43 White days, which made up the moderately priced days (€0.0948 for off-peak and €0.1125 for peak).
- c) 22 Red days, which made up the most expensively priced days (€0.1762 for off-peak and €0.4929 for peak).

Customers were notified which day would be in effect a day ahead through the use of the web, call centres, email subscriptions and a display device plugged into an electrical socket. EDF implemented a pilot programme, during which prices were much higher than the Tempo rate, before launching the Tempo rate on a full time basis. Own price elasticities for peak were estimated at -0.79 and off-peak at -0.18, much higher than any of the US pilot programmes. Filippini (1995) also found high elasticity estimates for the Swiss study.

2.9.7 Idaho Residential Pilot Programme – Idaho

The Idaho Power Company in the US initiated two residential pilot programmes in 2005 and 2006:

- a) TOD, which was designed as a conventional TOU programme where participants were charged different rates according to the time of day. On peak at \$0.083/kWh (weekdays 13h00 to 21h00), mid-peak at \$0.061/kWh (weekdays from 07h00 to 13h00) and off-peak at \$0.045/kWh (weekdays from 21h00 to 07h00, weekends and public holidays). The percentage of use for peak, mid-peak and off-peak to total (summer) use was the same for both control and treatment groups.
- b) Energy Watch, which was designed as a CPP pilot and participants notified of the CPP event on a day-ahead basis. 10 CPP days were called during 2006. CPP hours were at a rate of \$0.20/kWh (17h00 to 21h00) and non-CPP at a rate of \$0.054/kWh for the rest of the day.

The TOD rate had no effect on shifting use due to the very low ratio of peak to off-peak rates (1.84:1) – this suggests that a higher ratio of peak to off-peak rates is needed to induce customers to shift use. The average hourly load reduction for the 10 CPP days was 1.26kW with an average total load reduction for a 4-hour event of 5.03kW.

2.9.8 Energy Smart Pricing Plan – Illinois

This was the first large-scale Real-Time Pricing (RTP) pilot in the US and ran between 2003 and 2006. Up to 1 500 customers took part. The programme focused on low-cost technology and tested the hypothesis that “major benefits may result from RTP without the use of expensive technology”.. The design included a day-ahead announcement of hourly prices for the following day and high-price day notification via phone or email when the price (wholesale) exceeded \$0.10/kWh (increased to \$0.13/kWh threshold in 2006) with a price cap of \$0.50/kWh. Cycling switches were installed in participants’ homes. Indications of prices were by means of a glass orb (Energy PriceLight) that glowed in different colours (high and low prices) as well as an energy use campaign.

a) Programme results for 2005:

- The main purpose of the pilot was to determine the price elasticity of demand and energy conservation impacts.
- Regression analysis was used in a simple double-log specification using hourly use (dependent variable) and hourly prices and weather (independent variable) for the summer months.
- The overall price elasticity was estimated at -0.047 increasing to -0.069 with enabling technology.
- The largest response occurred on high-price days and participants were able to reduce their consumption by 15% compared normal flat rate tariff consumption.
- Price responsiveness varied throughout the day with own price elasticities by time of day ranging from -0.02 to -0.03.
- There was an overall net decrease in the participants’ consumption and an average of 35.2kWh per month reduction for the summer months (3% to 4% of summer use).

b) Programme results for 2006:

- The price elasticity during the summer of 2006 was estimated to be -0.047 when the price was equal to or below \$0.13/kWh, and increased to -0.082 (absolute value) when the price was above \$0.13/kWh.
- The Energy PriceLight improved customer responsiveness, resulting in an elasticity of -0.067 across all hours.
- Customers with HVAC cycling (enabling technology) increased the price elasticity estimate to -0.098.

2.9.9 Ameren UE CPP Pilot – Missouri

This was a residential TOU pilot study initiated in 2004 that evaluated the impacts of three different TOU programmes:

- a) TOU with peak rate of \$0.183/kWh from 15h00 to 19h00 on weekdays, mid-peak rate of \$0.075/kWh from 10h00 to 15h00 and 19h00 to 22h00 on weekdays, and off-peak rate of \$0.048/kWh from 22h00 to 10h00 weekdays as well as weekends and holidays. 88 treatment customers and 89 control customers took part.
- b) TOU-CPP with CPP rate of \$0.30/kWh 15h00 to 19h00 on weekdays (10 times per summer), peak rate of \$0.168/kWh from 15h00 to 19h00 on weekdays, mid-peak rate of \$0.075/kWh 10h00 to 15h00 and 19h00 to 22h00 on weekdays, and off-peak rate of \$0.048/kWh 22h00 to 10h00 on weekdays as well as weekends and holidays. 85 treatment customers and 89 control customers took part.
- c) TOU-CPP-Tech with enabling technology (smart thermostat). 77 treatment customers and 117 control customers took part.

During the first year of the pilot (June 2004 to September 2004) results showed that participants in the TOU and TOU-CPP did not shift a statistically significant amount of load from peak to mid-peak or off-peak, thus indicating no ‘needle peaks’ were formed. Off-peak consumption increased and peak consumption decreased slightly for both the treatment and control groups. The TOU-CPP-Tech group reduced their average CPP demand by 35% on event days compared to the control group, whilst the TOU-CPP group reduced their demand by 12% during the same period – both impacts being statistically significant at the 5% level. During the second year of the pilot (2005), the TOU-CPP-Tech group reduced their average CPP demand by 24% on 8 event days compared to the control group, and the TOU-CPP group reduced their demand by 13%.

2.9.10 GPU Pilot – New Jersey

GPU offered a residential TOU pilot programme with a CPP and enabling technology in 1997. Three price tiers were offered (peak, shoulder and off-peak) and a CPP only effective for a limited number of high-cost summer hours. The programme consisted of a control group and two treatment groups:

- a) Control group – standard increasing block tariff with \$0.12/kWh for consumption less than 600kWh/month and \$0.153/kWh for consumption greater than 600kWh/month.
- b) Treatment group 1 (high shoulder / peak design) – off-peak rate of \$0.065/kWh from 01h00 to 08h00 and 20h00 to 00h00 on weekdays, shoulder peak rate of \$0.175/kWh from 09h00 to 14h00 and 19h00 to 20h00 on weekdays, peak rate of \$0.30/kWh from 15h00 to 18h00 on weekdays and a CPP rate of \$0.50/kWh when called during peak period.
- c) Treatment group 2 (low shoulder / peak design) – off-peak rate of \$0.09/kWh from 01h00 to 08h00 and 20h00 to 00h00 weekdays, shoulder peak rate of \$0.125/kWh from 09h00 to 14h00 and 19h00 to 20h00 on weekdays, peak rate of \$0.25/kWh from 15h00 to 18h00 weekdays and a CPP rate of \$0.50/kWh when called during peak period.

An important feature of this pilot is that the treatment groups had equipment installed that allowed them to preset their use patterns in response to time-varying rates as well as receive signals from the utility during critical hours. Analysis of the hourly data reveals the following:

- a) On non-critical weekdays, treatment group customers reduced demand during peak periods by 0.53kW (26%) compared to the control group. The treatment group with the high rate design reduced by 50% more than the treatment group with the low rate design during each of the peak and shoulder periods.
- b) On CPP days, treatment group customers reduced demand by 1.24kW (50%) during the first hour of the peak period compared to the control group, with reductions decreasing over subsequent peak hours. The treatment groups' consumption was larger than the control group during the shoulder and off-peak periods, indicating some substitutability between periods.
- c) There was no significant average use difference between the treatment groups and control group.

The data from this programme was used for the estimation of the elasticities of substitution based on two different demand models – the CES and the Generalised Leontief (GL):

- The CES model yielded an estimate of 0.30, which was larger than that estimated in previous studies and could be attributed to the enabling technologies made available to customers (a summary of the estimates is presented in Table 2-2).
- The GL model (which allows estimates to vary between time periods) yielded an estimate of 0.40 between peak and off-peak periods.

Table 2-2: Substitution elasticity estimates – GPU pilot

Month	Time period	CES model	GL model	
			High rate	Low rate
1	Overall	0.306	-	-
	Peak to shoulder	-	0.155	0.166
	Peak to off-peak	-	0.395	0.356
	Shoulder to off-peak	-	0.191	0.187
2	Overall	0.295	-	-
	Peak to shoulder	-	0.055	0.06
	Peak to off-peak	-	0.407	0.366
	Shoulder to off-peak	-	0.178	0.176

Source: Faruqui and Sergici (2009)

2.9.11 PSE&G Residential Pilot Program – New Jersey

The Public Service Electric and Gas Company (PSE&G) of New Jersey offered a residential TOU / CPP programme during 2007 and 2007. The two sub-programmes were:

- myPower Sense* – consisted of 379 customers who were educated about the TOU / CPP and given notification of the CPP events on a day-ahead basis. These customers received a \$25 incentive upon enrolment and \$75 upon conclusion of the programme.
- myPower Connection* – consisted of 319 customers who were issued with free programmable communicating thermostats (PCT). The PCTs allowed price signals to be received from PSE&G and adjusted customer air conditioning settings based on programmed set points. These customers received \$75 upon conclusion of the programme as an incentive.

A total of 450 customers made up the control group. The TOU / CPP tariff included a night discount, a base rate, an on-peak 'adder' and a CPP 'adder' as described:

- Base price of \$0.09/kWh (June to September 2006) and \$0.087/kWh (June to September 2007) applicable all hours.
- Night discount of -\$0.05/kWh (June to September 2006) and -\$0.05/kWh (June to September 2007) applicable from 22h00 to 09h00 daily.
- On peak adder of \$0.08/kWh (June to September 2006) and \$0.15/kWh (June to September 2007) applicable 13h00 to 18h00 weekdays – added to base price.
- CPP adder of \$0.69/kWh (June to September 2006) and \$1.37/kWh (June to September 2007) applicable 13h00 to 18h00 and added to base price when called.

Two CPP events were called by PSE&G during the summer of 2006 and five during the summer of 2007:

- *myPower Sense* customers with Central Air Conditioning (CAC) reduced their peak demand by 3% on TOU days and 17% on CPP event days. The elasticity of substitution estimate was 0.069.
- *myPower Sense* customers without CAC achieved 6% reductions on TOU days and 20% on CPP days. The elasticity of substitution estimate was 0.063.
- *myPower Connection* customers reduced consumption by 21% on TOU days and an additional 26% on CPP days. The elasticity of substitution estimate was higher for these customers – 0.125 – mainly due to the enabling technology.

2.9.12 Energy Australia's Network Tariff reform – New South Wales

This was the largest demand management programme by Energy Australia and included a strategic pricing study started in 2005 with 650 residential customers taking part. The study tested seasonal, dynamic and information only tariffs and involved the use of in-house displays and online data access. Some of the participants also received dynamic peak price signals via SMS, telephone, e-mail or to the display unit. Results from the pricing programme showed there were minimal conservation effects from customers on TOU rates compared to customers on flat rate tariffs. The price elasticity estimates obtained during this programme are summarised in Table 2-3.

Table 2-3: Price elasticity estimates – Energy Australia

Season	Price elasticity estimates		
	Peak own price	Peak to shoulder cross price	Peak to off-peak cross price
Summer 2006	-0.30 to -0.38	-0.07	-0.04
Winter 2006	-0.47	-0.12	-

Source: Faruqui and Sergici (2009)

A summary of the findings from the Energy Australia tariff reform programme:

- a) Under dynamic peak pricing (DPP) customers reduced peak consumption by 24% for DPP high rates (Australian \$ 2+/kWh) and 20% for medium rates (Australian \$ 1+/kWh).
- b) Customers responded to the second DPP event more than the first, this could be attributed to the *day-ahead* notification given during the second DPP event as opposed to the *day-of* notification used for the first event.
- c) Response was also greater for the second event than for the third event, which could be explained by the lower temperatures for the third event day, resulting in customers being left with fewer discretionary appliances to turn off.

2.9.13 Ontario Energy Board’s Smart Price Pilot – Ontario, Canada

The Ontario Energy Board’s Smart Price Pilot was operated between August 2006 and March 2007 and tested the impact of three different price structures using a sample of customers:

- a) An existing Regulated Price Plan (RPP) TOU, which had an off-peak rate of Canadian Dollar (C\$) 0.035/kWh (22h00 to 07h00 on weekdays and on weekends and holidays), mid-peak rate of C\$0.075/kWh (07h00 to 11h00 and 17h00 to 22h00 on weekdays) and an peak rate of C\$0.105/kWh (11h00 to 17h00 on weekdays).
- b) RPP TOU rates with a CPP component (TOU-CPP) at which the CPP was set at C\$0.30/kWh based on the average of the 93 highest hourly Ontario electricity prices in the previous year. The RPP TOU off-peak price was decreased to C\$0.031/kWh to offset the increase in the CPP. The maximum number of critical days was set at 9 and only 7 were called during the pilot.

- c) TOU CPR, which was a critical peak rebate providing customers with a C\$0.30/kWh for each kWh of reduction from baseline. The CPR baseline was defined as 1.25 of the average use during the participants' last five non-event weekdays.

A total of 373 customers participated in the pilot – 124 TOU only, 124 TOU-CPP, 125 TOU-CPR and 125 in the control group. The control group had smart meters installed but continued to pay non-TOU rates. Results from the programme showed:

- A load shift of between 5.7% and 25.4% during the four summer CPP events.
- A load shift of between 2.4% and 11.9% during the entire peak period of the four summer events.

2.9.14 Puget Sound Energy TOU programme – Washington

The Puget Sound Energy TOU programme involved some 300 000 customers (residential and small commercial) and was initiated in 2001. It had a rate design involving four price periods – morning, midday, evening, and economy periods. Peak prices were 15% higher than the average prices prior to the programme, and off-peak prices were 15% lower. Customers were given the option of reverting to standard rates if they were not satisfied with the programme upon its completion. Customers initially saved \$0.20 but as there was a \$1.00 meter reading cost, customers ended up paying in \$0.80. This was in contrast to the first year in which customers paid no meter reading costs and 55% of them had electricity savings. The programme was terminated due to customer dissatisfaction and negative media coverage. Some lessons can, however, be learnt from this pilot:

- a) A modest price differential between peak and off-peak may induce customers to shift load under unusual circumstances (energy crisis of 2001 in the West). An independent analysis of the programme showed that customers lowered their peak use by 5% per month over a 15 month period.
- b) Customers must be provided with accurate expectations about their bill savings.
- c) A pilot programme is essential before implementing a full-scale rollout.

2.9.15 The Olympic Peninsula Project – Washington

This was a project that tested whether automated two-way communication systems between grid and passive resources (end use loads and idle distributed generation) and the use of price signals were effective in reducing system constraints. Potential participants were recruited who had high-speed Internet access, electric HVAC systems, electric water heaters and

electric clothes dryers. 112 homes had two-way communication systems installed that allowed utilities to send pricing signals and customers to pre-program their demand response preferences. These were then equally divided into one control and three treatment groups. Equipment was installed at the control group but they were given no other additional information. Each treatment group was assigned one of three contracts:

- a) Fixed prices at \$0.081/kWh applicable all hours and seasons.
- b) Summer: Off-peak rate of \$0.05/kWh from 09h00 to 15h00, peak rate of \$0.135/kWh from 15h00 to 21h00, CPP at \$0.35/kWh when called. Spring/Fall/Winter: Off-peak rate of \$0.04119/kWh from 09h00 to 18h00 and 21h00 to 06h00, peak rate of \$0.1215/kWh from 06h00 to 21h00 and 18h00 to 21h00, CPP at \$0.35/kWh when called.
- c) RTP where prices were unpredictable and varied every 5 minutes. Participants in this contract responded to the RTP by presetting their preferences through the web, they also had an option to override their preferences at any time.

Results from the pilot showed the following:

- The fixed price group saved 2% compared to the control group whilst the TOU-CPP saved 30% and the RTP group 27%.
- The TOU group also saved 21% of energy consumption compared to the control group.
- Examination of the residential load shapes by contract and season showed that the TOU-CPP contract was the most effective at reducing peak demand.
- On average the RTP contract did not bring about the lowest average peak demand.

2.10 Conclusion

The literature review conducted revealed that the price elasticity of demand for electricity for most developed and developing countries is inelastic, indicating that as prices increase, the demand does not decrease significantly. Long-term price and income elasticity estimates for SA are inelastic.

The review also highlighted the fact that long-term estimates are larger than short-term estimates due to consumers being able to make long-term adjustments to appliance holdings but limited adjustments in the short term. In the short term appliance ownership is fixed and the only response to changes in prices is customer behaviour. Furthermore, as income levels increase so too does the demand for electricity as many communities move away from

traditional fuels such as paraffin and place more reliance on electricity. Households at a higher level of appliance ownership exhibit larger elasticities due to the diversity of appliance use than customers with lower levels of appliance ownership. Households with lower incomes are more sensitive to electricity price changes than those with higher income levels since the lower-income families allocate a larger portion of their total expenditure to this cost. Electricity consumption is strongly influenced by changes in climatic conditions particularly when consumers have high levels of weather-sensitive appliances such as air conditioners and electric space heaters.

The review further highlighted the fact that time-varying tariffs (such as TOU and CPP) more accurately reflect the cost of supply and improve the efficiency of resource allocations of generating plant, by sending the right price signals to consumers, than flat rate tariffs. Time-varying rates provide an incentive to consumers to alter consumption patterns by shifting use from peak to off-peak.

The review shows that the ‘elasticity of substitution’ is a function of price elasticity and is used in the analysis of TOU and other time-variant pricing experiments. It is a measure used to predict the change in the ratio of peak to off-peak energy use given a change in ratio of peak to off-peak prices and therefore in determining the shift in daily and hourly consumption use from higher priced peak periods to lower priced off-peak periods. The models used in determining the elasticity of substitution estimates include the CES and the GL forms. The methods used in the analysis include the OLS regression method as well as standard statistical tools to analyse the data.

The literature highlights the price differential as the main contributing factor in the ‘substitutability’ of peak and off-peak consumption and hence the magnitude of the elasticity of substitution estimates. Estimates increase with the inclusion of ‘conditioning variables’ such as the ownership levels of major appliances, levels of income per household, temperature variations and socio-demographic factors in the analysis. An increase in the number of household residents inversely affects the elasticity of substitution estimates between peak and off-peak consumption. The impact of enabling technologies is significant as this determines the extent of consumers’ reactions to pricing signals. There is a greater response with enabling technologies than without.

The literature identified the methodological approach to the analysis of time-varying residential tariffs conducted by many utilities around the world. Data is in the form of hourly-metered consumption per customer. The experiment consists of a treatment group, which is placed on TOU rates, and a control group, which remains on standard rates. The data from each group is then used to form panel datasets per experimental area/s.

CHAPTER THREE : EXPERIMENTAL TIME-OF-USE TARIFF

The previous chapter reviewed the literature on various aspects regarding residential electricity pricing. This chapter reviews the experimental TOU tariff pilot conducted by Eskom from 1998 to 2003. The objective of this chapter is to gain an understanding of the tariff design as well as the findings of the pilot.

Section 3.1 presents a brief introduction to the chapter. **Section 3.2** reviews the experimental tariff design in terms of the rates that were in effect as well as the electricity prices for these rates. **Section 3.3** reviews the methodology used in the analysis of the impact of this tariff in two of the main pilot areas. The pilot results are also summarised in this section. **Section 3.4** concludes this chapter.

3.1 Introduction

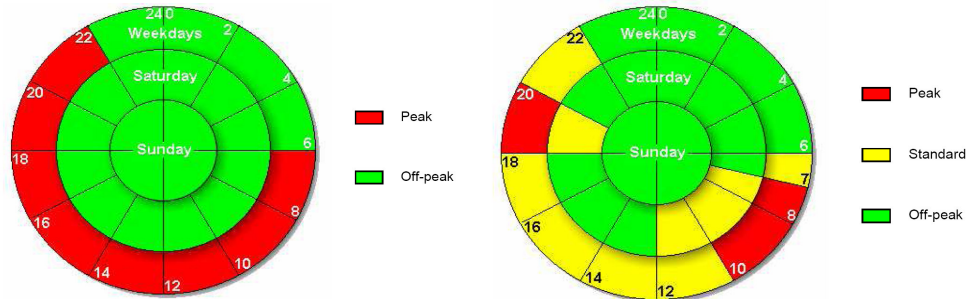
Eskom tested a residential TOU tariff at various sites around SA over the period 1998 to 2003. The pilot tariff was referred to as the HomeFlex tariff and was based on the same peak and off-peak times as large power user tariffs for industrial and commercial customers. The sites that were chosen included Sandton (Johannesburg) and Tableview (Cape Town). Each site consisted of a control group, a two-part TOU sample and a three-part TOU sample. The project objectives were to: 1) perform a statistical analysis of the effect of this tariff on customers' load profiles, peak demand reduction and any changes in consumption patterns; 2) analyse the effect of the tariff on the Distribution as well as the National network; and 3) to estimate the effects of the tariff signal on the After Diversity Maximum Demand.

3.2 Pilot tariff design

The HomeFlex TOU pricing pilot was designed to test residential customer reaction in terms of electricity use across different time periods, by pricing these time periods differently. The time periods were aligned to the Eskom-defined time periods (see Figure 3-1 for a description) and consisted of peak, standard and off-peak periods. These periods were in effect for weekdays and weekends as well as across seasons, i.e., winter periods (high season) and summer periods (low season). Residential peak demand in SA is higher during

the winter months (June to August) than the summer months (September to May) primarily due to space heating during evening periods (NERSA, 2005).

Figure 3-1: Eskom-defined time periods



Source: Eskom (2007)

The alignment of the HomeFlex tariff to the peak and off-peak periods defined by Eskom is presented in Table 3-1. The experiment involved the testing of a two- and three-part tariff. The two-part tariff (T2) was designed with two rates, i.e., a weekday morning and evening peak rate and an off-peak period rate. All hours for the weekend were regarded as off-peak. The three-part tariff (T3) was more complicated and was designed to include three rates, i.e., daily morning and evening peaks, three shoulder rates for weekdays and weekends (standard rate) and weekday and weekend off-peak periods.

Table 3-1: Alignment of HomeFlex to defined time periods

Time period	TOU period				
	3 part TOU (T3)			2 part TOU (T2)	
	Weekday	Sat	Sun	Weekday	Weekend
00:00 to 06:00	off-peak	off-peak	off-peak	off-peak	off-peak
06:00 to 07:00	standard	off-peak	off-peak	off-peak	off-peak
07:00 to 10:00	peak	standard	off-peak	peak	off-peak
10:00 to 18:00	standard	off-peak	off-peak	off-peak	off-peak
18:00 to 20:00	peak	standard	off-peak	peak	off-peak
20:00 to 22:00	standard	off-peak	off-peak	off-peak	off-peak
22:00 to 00:00	off-peak	off-peak	off-peak	off-peak	off-peak

Source: Dekenah et al (2004)

The tariff prices that were experimented with during 2001 and 2002 for each of the rates are presented in Table 3-2. As can be seen, higher prices were charged during the peak period than the off-peak period. The prices were adjusted in 2002 to reduce the price differential between peak and off-peak periods.

Table 3-2: HomeFlex experimental energy charges

Tariff	Season	Period	Year	
			2001	2002
T3	Low	peak	23.33	24.06
	Low	standard	19.43	18.16
	Low	off-peak	15.60	15.36
	High	peak	70.06	63.33
	High	standard	26.57	23.02
	High	off-peak	17.12	16.38
T2	Low	peak	15.94	19.07
	Low	off-peak	10.31	11.83
	High	peak	62.77	58.34
	High	off-peak	14.85	14.92

Source: Dekenah et al (2004)

3.3 Engineering analysis of the impact of the HomeFlex tariff

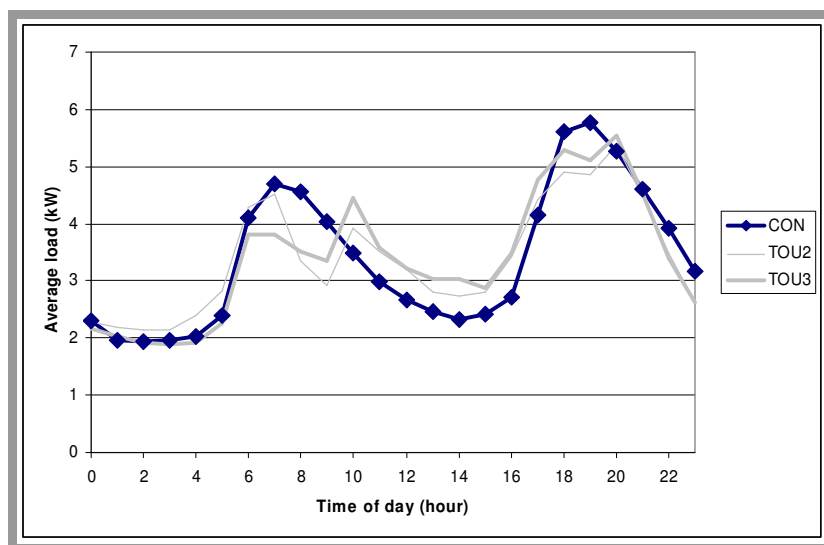
Dekenah et al. (2004) analysed the impact that the HomeFlex tariff had in causing customers in the pilot project to shift consumption from peak to off-peak periods. Their analysis followed a purely engineering approach. Load data was collected from energy meters installed at each customer point and uploaded to the HomeFlex database. The data was filtered and datasets formulated for each treatment group and the control group within the experiment. Aggregate profiles were then formed and the analysis was made by comparing the treatment and control group profiles. The main experimental area was Sandton (located in Johannesburg, SA) and Tableview (located in Cape Town, SA).

3.3.1 The Sandton TOU experiment

This area was represented by 123 residential customers, divided into three groups: 46 control customers (standard rates), 37 customers on the T2 TOU experimental rate and 40 customers on the T3 TOU experimental rate. Treatment customers were fitted with load profiling energy meters to record their hourly consumption (kWh) as well as enabling technology in the form of time switches that controlled the ‘on’ and ‘off’ times of Hot Water Cylinder (HWC) loads. The time switches were programmed in synchronicity with Eskom-defined peak periods (07h00 to 10h00 for the morning peak and 18h00 to 20h00 for the evening peak) and were set to switch off the HWCs during these periods. The time switches had an override facility to best suit the lifestyle of individual customers.

The effect of the tariff on the treatment groups when compared to the control group was significant as shown by Figure 3-2. This also suggests that most of the effect was probably due to the operation of the time switches. The Sandton pilot had an average consumption of 2 200kWh/month; Sandton can be regarded as a high-income area. There was a load shift of 0.8 to 1.0kW of demand out of the peak periods (20% reduction compared to control group), (Dekenah et al., 2004).

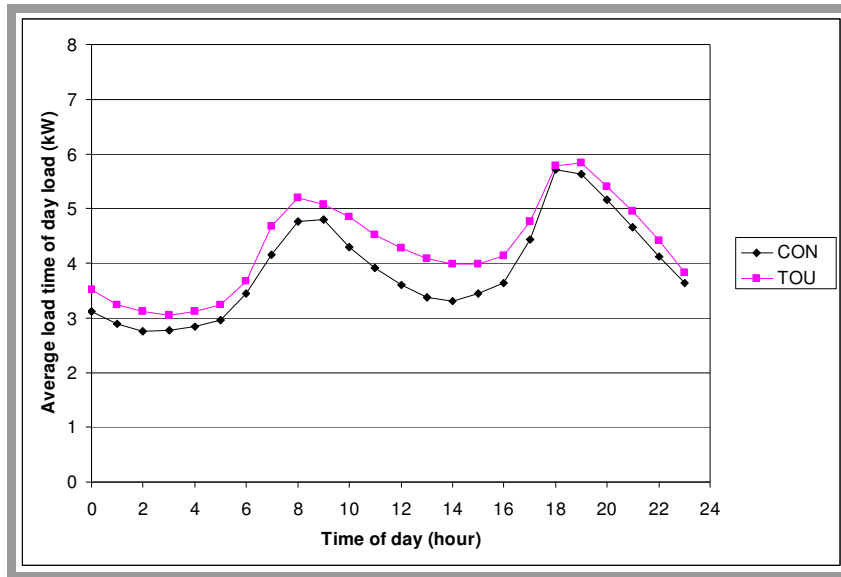
Figure 3-2: Response by Sandton customers to TOU rates – high season, weekday profile



Source: Dekenah et al. (2004)

Dekenah (2004) concludes that the analysis of weekend consumption patterns revealed no distinguishable difference between the treatment and control groups. However, as shown by Figure 3-3, there is a distinguishable difference in profile patterns and the consumption levels of treatment customers (TOU) appear consistently larger than control customers throughout weekend hours.

Figure 3-3: Response by Sandton customers to TOU rates – high season, weekend profile

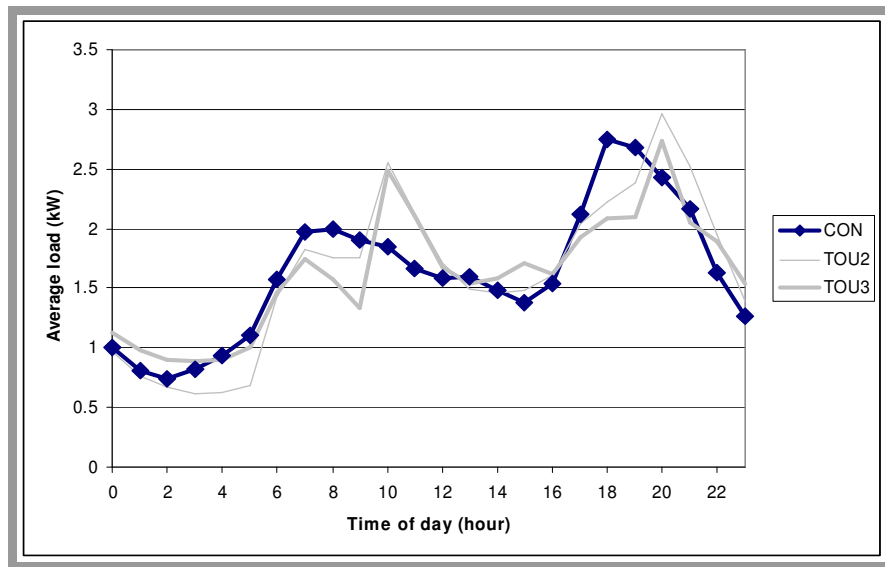


Source: Dekenah et al. (2004)

3.3.2 The Tableview TOU experiment

This area was represented by 149 residential customers, divided into three groups: 50 control customers (standard rates), 49 customers on the T2 TOU experimental rate and 50 customers on the T3 TOU experimental rate. Treatment customers were fitted with load profiling energy meters to record their hourly consumption (kWh). HWC loads were controlled by utility-triggered load control relays (ripple). The relays were triggered in accordance with Eskom-defined peak periods and were set to switch off the HWCs from 07h00 to 10h00 (morning peak) and 18h00 to 20h00 (evening peak) for both weekdays and weekends, except Sundays. The response by the treatment group compared to the control group was significant as shown in Figure 3-4. Customers in the Tableview pilot had an average consumption of 900kWh/month; the area can be regarded as a middle-income area. There was a load shift of 1 to 1.2kW out of the peak periods (30% reduction compared to control group) (Dekenah et al., 2004).

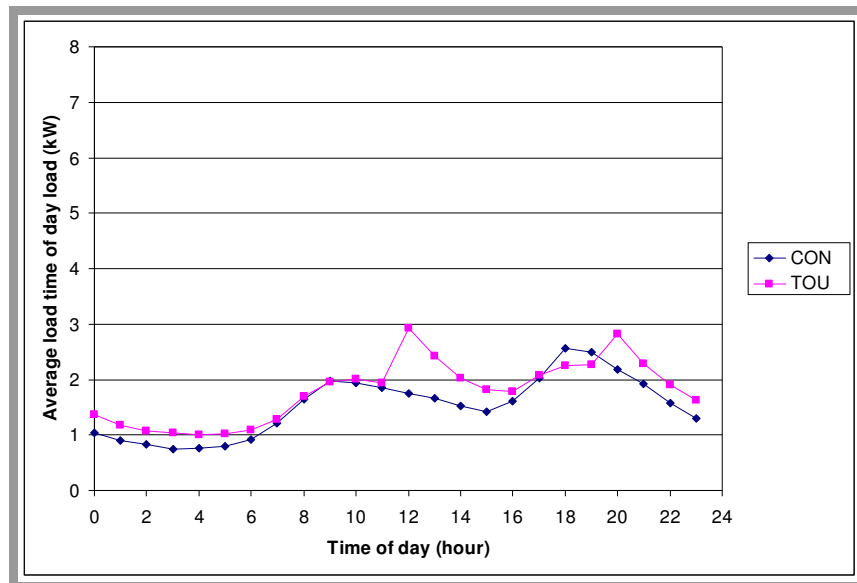
Figure 3-4: Response by Tableview customers to TOU rates – high season, weekday profile



Source: Dekenah et al. (2004)

Dekenah (2004) concludes that the analysis of the weekend consumption patterns for Tableview customers revealed no distinguishable difference between the treatment and control groups. However, as shown by as shown by Figure 3-5, there is a distinguishable difference in the profile patterns and the consumption levels of treatment customers (TOU). There is not, however, a consistent difference of treatment from control customers throughout the weekend hours as was the case for Sandton customers.

Figure 3-5: Response by Tableview customers to TOU rates – high season, weekend profile



Source: *Dekenah et al. (2004)*

3.4 Conclusion

The HomeFlex residential TOU pricing pilot experiment, which was conducted by Eskom during the period 1998 to 2003, proved to be successful. The engineering analysis revealed that the overall load reduction from the treatment groups during the weekday peak periods was due to the TOU tariff. Treatment customers also consumed more over the weekend periods than did the control customers. The analysis was done from an engineering point of view and no price elasticity estimates were calculated.

All the treatment groups were fitted with enabling technologies that switched off HWC loads during the peak periods. The overall impacts of the experimental tariff may be attributed to this and the fact that the customers did not adjust or bypass these devices. Data for 96 control customers on standard rates, 86 customers on a T2 TOU tariff and 90 customers on a T3 TOU was collected over the period 2001-2003 and stored in the HomeFlex database. The database currently resides with the Sustainability and Innovations department, Eskom Research Division.

CHAPTER FOUR : METHODOLOGY FOR ECONOMETRIC ANALYSIS

The previous chapter reviewed the experimental TOU tariff pilot project and the *engineering* results from this pilot. This chapter focuses on the methodology, identified in the literature, for the *econometric* assessment of TOU pricing.

Section 4.1 presents a brief introduction to the chapter. **Section 4.2** presents the theoretical framework for the econometric approach. **Section 4.3** specifies the model and functional form. **Section 4.4** summarises the model and substitution equations. **Section 4.4** concludes the chapter.

4.1 Introduction

Early studies in analysing the response of residential customers to TOU pricing followed a purely econometric analysis methodology and include Caves et al. (1984a), Taylor and Schwarz (1990) and Baladi et al. (1998). Exceptions are to be found in the work of Kahn et al. (1986) whose approach in this regard combined an econometric approach with an engineering approach. After reviewing a variety of model specifications, the CES demand system was decided upon for this study. Other structural models include the log-log formulation, the quadratic demand system as well as the GL demand system. The CES demand system was chosen as it is able to model a variety of behavioural changes for customers on time-varying pricing such as TOU:

- 1) A reduction in peak period energy use with no change in off-peak energy use can be seen as a reduction in the *ratio* of peak to off-peak energy use in the substitution equation.
- 2) An increase in off-peak energy use with no change in peak energy use can also be seen as a change in this ratio.

4.2 The theoretical framework

Early work with the CES demand system and related methodology for the econometric assessment of TOU pricing is to be found in Caves et al. (1984a). Known as the Caves and Christensen approach, this neoclassical model divides customer response to TOU pricing rates in three stages: Stage 1 models the changes in a customer's use share consumed during

on peak hours (for non public holiday weekdays and indicates changes in weekday load shape); Stage 2 models shifts in loads between weekdays and weekends; and Stage 3 models changes in the overall level of electricity expenditures. The model begins by expressing the indirect utility function (Caves et al., 1984a, 183-188:

$$V = V(P_i[P_w(P_p, P_o), P_h], P_g, Y) \quad (4-1)$$

where:

- V = consumer utility
- P_i = price index for total seasonal electricity usage
- P_w = price index for weekday electricity usage
- P_p = price of weekday peak electricity usage
- P_o = price of weekday off peak electricity usage
- P_h = price of weekend electricity usage
- P_g = price of non - electricity goods
- Y = total expenditures

Equation (4-1) expresses the consumer's utilisation choices as a function of electricity prices. To obtain a relationship to a function of electricity use, the demand equation for K_p is obtained by applying Roy's identity (Caves et al., 1984a):

$$K_p = \frac{V_i T_w W_p Y}{\sum_i V_i T_w W_i P_i + V_i T_h P_h + V_g P_g} \quad (4-2)$$

where:

- K_p = peak usage for weekdays
- $V_i = \partial V / \partial P_i$, (4-3)
- $V_g = \partial V / \partial P_g$, (4-4)
- $T_w = \partial P_i / \partial P_w$, (4-5)
- $T_h = \partial P_i / \partial P_h$, (4-6)
- $W_i = \partial P_w / \partial P_i, i = p, o$. (4-7)

And off-peak use for weekdays, K_o , is given by:

$$K_o = \frac{V_t T_w W_o Y}{\sum_i V_t T_w W_i P_i + V_t T_h P_h + V_g P_g} \quad (4-8)$$

The first stage can then be modelled by equation (4-9) which gives the peak to off-peak consumption on weekdays:

$$\frac{K_p}{K_o} = \frac{W_p}{W_o} \quad (4-9)$$

Letting E_w denote weekday expenditures then:

$$E_w = K_p P_p + K_o P_o = \frac{(V_t T_w W_p P_p + V_t T_w W_o P_o) Y}{\sum_i V_t T_w W_i P_i + V_t T_h P_h + V_g P_g} \quad (4-10)$$

Weekend electricity use, K_h can be expressed as:

$$K_h = \frac{V_t T_h Y}{\sum_i V_t T_w W_i P_i + V_t T_h P_h + V_g P_g} = \frac{V_t T_h Y}{V_t T_w P_w + V_t T_h P_h + V_g P_g} \quad (4-11)$$

And weekend expenditures E_h can be expressed as:

$$E_h = K_h P_h = \frac{V_t T_h P_h Y}{V_t T_w P_w + V_t T_h P_h + V_g P_g} \quad (4-12)$$

Thus stage 2 of the model is provided by the ratio of weekday to weekend expenditures and is given by:

$$E_w / E_h = \frac{T_w (W_p P_p + W_o P_o)}{T_h P_h} = \frac{T_w P_w}{T_h P_h} \quad (4-13)$$

where:

$$P_w = W_p P_p + W_o P_o \quad (4-14)$$

Thus E_w/E_h is a function of only the weekday price index P_w and the weekend price P_h . The total electricity expenditure faced by a household, E_t , is a function of peak expenditure and off-peak weekday expenditure (E_w) and weekend expenditure (E_h) and is given by:

$$E_t = E_w + E_h \quad (4-15)$$

$$E_t = (K_p P_p + K_o P_o) + K_h P_h \quad (4-16)$$

Substituting for E_w and E_h from equations (m) and (o):

$$\begin{aligned} E_t &= \frac{(V_t T_w W_p P_p + V_t T_w W_o P_o + V_t T_h P_h)Y}{V_t T_w P_w + V_t T_h P_h + V_g P_g} \\ &= \frac{V_t P Y}{V_t T_w P_w + V_t T_h P_h + V_g P_g} \end{aligned} \quad (4-17)$$

And expenditures on other goods E_g are given by:

$$E_g = \frac{V_g P_g Y}{V_t T_w P_w + V_t T_h P_h + V_g P_g} \quad (4-18)$$

Stage 3 of the model is thus provided by the ratio of electricity expenditures to other goods and is given by:

$$E_t / E_g = V_t P_t / V_g P_g \quad (4-19)$$

4.3 The model specification and choice of functional form

In order for the model to represent the full range of substitution possibilities between two commodities (peak and off-peak use), a functional form is needed to represent each stage. The CES form (Caves et al., 1984b; Baladi et al., 1998) is chosen to represent each stage:

The CES functional form is written as:

$$P = (u P_1^\rho + (1-u) P_2^\rho)^{1/\rho} \quad (4-20)$$

P_1 and P_2 are the two prices of two commodities represented by X_1 and X_2 , by applying Roy's identity the consumption ratio of the two commodities (Caves et al., 1984b) is:

$$X_1 / X_2 = (\partial P / \partial P_1) / (\partial P / \partial P_2) = u P_1^{\rho-1} / (1-u) P_2^{\rho-1} \quad (4-21)$$

Substituting for:

$\alpha = \ln(u/(1-u))$ and $\beta = 1 - \rho$ the consumption ratio of commodity X_1 to commodity X_2 is simplified through the natural log expression:

$$\ln(X_1 / X_2) = \alpha - \beta \ln(P_1 / P_2) \quad (4-22)$$

Following Baladi et al. (1998), the three-stage system of equations, for commodity X_1 and X_2 representing commodities from equation (4-8) – weekday peak consumption (K_p) to weekday off-peak consumption (K_o); equations (4-10) and (4-12) – representing total weekday electricity expenditures (E_w) and total weekend as well as holiday expenditures (E_h); equations (4-17) and (4-18) – total electricity expenditures (E_t) and total non-electricity expenditures (E_g) respectively. P_1 and P_2 represent peak (P_p) and off-peak prices (P_o) respectively:

$$\ln(K_p / K_o) = \alpha_1 - \beta_1 \ln(P_p / P_o) \quad (4-23-i)$$

$$\ln(E_w / E_h) = \alpha_2 + (1 - \beta_2) \ln(P_w / P_h) \quad (4-23-ii)$$

$$\ln(E_t / E_g) = \alpha_3 + (1 - \beta_3) \ln(P_t / P_g) + \theta \ln(Y / P_g) \quad (4-23-iii)$$

where:

$$\alpha_i = \ln[u_i / (1 - u_i)] \quad i = 1, 2$$

$$\alpha_3 = \ln\{u_3 \rho_t / [(1 - u_3) \rho_g]\}$$

$$\beta_3 \equiv 1 - \rho_t$$

$$\theta \equiv \rho_g - \rho_t$$

Equation (4-23-i) models the shape of weekday use between the peak and off-peak pricing periods. Under standard flat rates there is no price differential, i.e., $P_p = P_o$, thus from equation (4-23-i):

$$\begin{aligned}\ln(K_p / K_o) &= \alpha_1 - \beta_1 \ln(1/1) \\ \ln(K_p / K_o) &= \alpha_1\end{aligned}\tag{4-24}$$

Therefore α_1 denotes the log ratio of peak to off-peak consumption under standard flat rates. α_1 is positive when peak consumption is higher than off-peak consumption and negative when peak consumption is less than off-peak consumption under standard tariffs. The coefficient β_1 measures the partial Allen elasticity of substitution between peak and off-peak use. The larger the value of β_1 , the greater the reduction in the peak to off-peak period use ratio in response to an increase in TOU peak to off-peak price ratios (Baladi et al., 1988).

Similarly the parameters of stage 2 of the model (equation (4-23-ii)) can be interpreted by α_2 measuring the ratio of weekday to weekend use under standard flat rate tariffs (i.e., $P_w = P_h$ – no difference in weekday and weekend use shares) and β_2 , the partial Allen elasticity of substitution between weekday and weekend use. This is the distribution of expenditure between weekdays and weekends (including holidays) due to TOU pricing.

Equation (4-23-iii) is stage 3 of the model and represents a household's allocation of income (Y) between electricity and other goods. Unlike stages 1 and 2, this stage is only a function of income (Y). The price index for non-electricity goods (P_g) is normalised to equal the standard rate for electricity and income is also normalised so that $Y = P_g$ for the average household. The natural log ratio of electricity to non-electricity expenditures is thus denoted by α_3 . The full Allen elasticity of substitution between electricity and other goods is given by Baladi et al. (1988) as:

$$\sigma_{tg} = \beta_3 - \theta w_t\tag{4-25}$$

and the income elasticity for electricity is given by:

$$\eta_{ty} = 1 + \theta(1 - w_t)\tag{4-26}$$

where:

- σ = full Allen elasticity of substitution
- β = partial Allen elasticity of substitution
- w_t = share of total expenditures allocated to electricity
- η_y = income elasticity of demand
- θ = fixed effect coefficient

4.4 Summary of the Caves and Christensen three-stage model

- a) Stage 1 – analysis of the ratio of peak to off-peak consumption as a function of conditioning variables and the ratio of peak to off-peak prices:

$$\ln(K_p / K_o) = \alpha_1 + \sum_i \gamma_{1i}(D_i) - [\beta_1 + \sum_i \delta_{1i}(D_i)] \ln(P_p / P_o) \quad (4-27)$$

- b) Stage 2 – analysis of the ratio of weekday to weekend consumption as a function of conditioning variables and the ratio of weekday to weekend prices:

$$\ln(E_w / E_h) = \alpha_2 + \sum_i \gamma_{2i}(D_i) + \{1 - [\beta_2 + \sum_i \delta_{2i}(D_i)]\} \ln(P_w / P_h) \quad (4-28)$$

- c) Stage 3 – analysis of the ratio of the expenditure on electricity to the expenditure on other goods, as a function of conditioning variables, and the ratio of the price of electricity to the price of other goods:

$$\begin{aligned} \ln(E_t / E_g) = & \alpha_3 + \sum_i \alpha_{3i}(D_{yi}) + \sum_i \gamma_{3i}(D_i) + \{1 + [\beta_3 + \sum_i \delta_{3i}(D_i)]\} \ln(P_t / P_g) \quad (4-29) \\ & + [\gamma_{TOU} + \sum_i \gamma_{TOUi}(D_i)](D_{TOU}). \end{aligned}$$

4.5 Conclusion

The Caves and Christensen (1984a) approach involves the utilisation of the CES demand system and provides 3 stages of analysis. This demand system provides a generally acceptable model for the econometric assessment of TOU pricing.

Stage 1 analyses the ratio of peak to off-peak consumption as a function of peak to off-peak prices and other variables in order to determine the shift in use between these periods. Thus the ‘substitutability’ between peak and off-peak period consumption is established. The dependent variable in this stage is the natural log of the ratio of peak to off-peak consumption $\ln (K_p/K_o)$. The independent variables are: 1) the natural log of the ratio of peak to off-peak prices $\ln (P_p/P_o)$; and 2) other conditioning variables (D_i).

Stage 2 analyses the ratio of weekday consumption to weekend consumption as a function of peak to off-peak prices and other variables. Any shift of weekday consumption to weekend consumption is established and thus, the ‘substitutability’ between these consumption periods. The dependent variable in this stage is the natural log of the ratio of weekday to weekend consumption $\ln (E_w/E_h)$. The independent variables are: 1) the natural log of the ratio of peak to off-peak prices $\ln (P_w/P_h)$; and 2) other conditioning variables (D_i).

Stage 3 of the model analyses the ratio of electricity expenditure to the expenditure of other goods as function of the price or cost of electricity in relation to the price of other goods and is expressed as a function of household income. The dependent variable in this stage is the natural log of the ratio of electricity expenditure to the expenditure on other goods $\ln (E_e/E_g)$. The independent variables are: 1) the natural log of the cost of electricity to the cost of other goods $\ln (P_e/P_g)$; and 2) other conditioning variables (D_i).

The conditioning variables are those variables that may be expected to influence residential customer behaviour towards TOU pricing and include appliance ownership, socio-demographics and climatic conditions. Socio-demographic modifiers such as appliance ownership are expressed as binary variables with ‘1’ denoting ownership of a specific appliance and ‘0’ for non-ownership. The variation in climatic conditions is represented by the number of heating (or cooling) degree days (or hours) and is a function of a standard base temperature and ambient minimum / maximum daily (or hourly) temperatures.

CHAPTER FIVE : DATA FOR ECONOMETRIC ANALYSIS

The previous chapter identified the methodology to be used in the econometric analysis of TOU pricing. This chapter focuses on the data that is required for the analysis and, in particular, for the testing of the hypothesis.

Section 5.1 presents a brief introduction to the chapter. **Section 5.2** identifies the four major categories required for a panel data set, namely, customer load data, prices that were in effect for the experimental tariff, data on customer characteristics and, finally, climate variation data. **Section 5.3** summaries the econometric parameters and notation and **Section 5.4** concludes the chapter.

5.1 Introduction

The earliest literature on residential demand can be found in the work of Houthakker (1951) who analysed the demand for electricity in the United Kingdom by using cross-sectional data. This is a type of one-dimensional set that refers to data that is collected by observing many subjects (such as individual customer's electricity use levels) at the same point in time. Analysis of cross-sectional data involves comparing the differences across subjects. Time-series data is a sequence of time-spaced data points measured at successive uniform intervals. A combination of time-series and cross-sectional data is also referred to as panel data and is a two-dimensional data set (Wikipedia, 2009c). Analysis of panel data involves the aggregating of individuals' behaviour over a period of time (such as multiple customers in a TOU experiment observed over a sample period).

5.2 Panel data sets

Houthakker (1973) was among the first to use panel data for analysis, specifically for the residential sector. Studies that involved the specific analysis and impact of time-variant experimental pricing for residential customers using panel data included Aubin et al. (1995) for the econometric assessment of a six-rate RTP experiment by EDF, Baladi et al. (1998) in their analysis of a voluntary TOU experimental tariff in the US, and Akmal and Stern (2001) in their econometric assessment of residential energy in Australia. These studies relied on the following for an econometric assessment:

- 1) Customer load data such as metered consumption profiles for every customer in the experiment from which peak consumption (kWh) and off-peak consumption (kWh) data could be determined.
- 2) Electricity prices such as the TOU tariff prices, e.g., peak and off-peak period prices for the treatment groups and standard rate prices for the control groups.
- 3) Customer characteristics such as those obtained by surveys that included demographic information such as appliance ownership, consumption levels, income per household, number of residents per household, age of household head, etc.
- 4) Climate data such as daily minimum and maximum temperatures for the geographic areas in the experiments.

5.3 Customer load data

The main load data for each treatment and control customer, in both the Sandton and Tableview areas, consisted of 24 values per day of 60 minute integrated demand values obtained from energy meters installed at each customer supply point. The meters were configured to measure and store date / time stamped electrical active demand (kW) readings. This profile data was then downloaded from the meter at regular intervals over the course of the pilot duration by field staff and then uploaded to the HomeFlex database. This was a database that was created in Microsoft SQL 2000 (SQL 8.0) solely for the HomeFlex residential pricing project. The database was thus able to hold over two years of load profile data for each customer in the pilot for both the Sandton and Tableview areas.

In order to source the panel data needed for analysis, an understanding of the HomeFlex database structure was required. First the tables that contained key record fields were identified. The tables are summarised in Table 5-1.

Table 5-1: HomeFlex database key Tables

Table	Description	Record
GROUP	Defines group codes	T2 (two-part TOU), T3 (three-part TOU) and CON (control group)
SITE	Defines site codes	S (Sandton), T (Tableview)
UTSMETER	Description of meter parameters	MTR_ID (meter identification), MTR_INTLEN (integration time in minutes)
UTSCUSTMER	Description of customers in the pilot sites	CST_ID (customer identification), CST_TOU (control, two- or three-part TOU), CST_ACCTNUM (customer conventional account number)
TOU_TIMES	Defines TOU periods	1 (peak), 2 (standard), 3 (off-peak)
TOU_RATES	List of energy charges for tariff	HF1&HF3 (three-part tariff with peak, off-peak and standard rates, high and low season, 2001-2002); HF2&HF4 (two-part tariff with peak and off-peak, high and low season, 2001-2002)
UTSPROFILE_SAST	Hourly power consumption per customer	Date / time stamp (CCYYMMDDHH) and average power (kW) reading for each customer in the experiment

Source: Dekenah (2004)

These existing tables and records were then compared with the HomeFlex database relationship diagram (Appendix F1) that allowed further extraction of data to take place by means of Microsoft (MS) SQL database queries. An example of such a query appears in Appendix F2. The purpose of the query was to extract consumption profiles for each treatment and control customer for both Sandton and Tableview. The sample period selected was for the winter months of 2001, i.e., June 2001 to August 2001. Three months were selected in order to simplify the analysis as well as focus the study on the high demand months of the year (winter months). The query produced a text file, which was then imported into a MS Excel spreadsheet for further manipulation of values.

The spreadsheet contained average demand readings (kW) over the sample period for weekday peak, weekday off-peak and weekend off-peak hours. An example of the raw data file spreadsheet is shown in Table 5.2. Thus time-series cross-sectional data for each control and treatment customer in both the Sandton and Tableview was available for further manipulation.

Table 5-2: Example of raw data file generated by query

Num	CST_GROUP – Control (CON) or Treatme nt (TOU)	CST_NAME	TOU_PERIOD	WeekDay (WK) Or Weekend (WE)	Sitecode – Tableview(T) or Sandton (S)	Average demand in period (kW)	Reading Count for total sample period in hours
1	CON	Cust. A	Peak	WK	T	2.834	330 (5)
			Off-peak	WE	T	1.897	624 (48)
			Off-peak	WK	T	1.748	1254 (19)
2	TOU	Cust. B	Peak	WK	T	1.510	330 (5)
			Off-peak	WE	T	0.692	624 (48)
			Off-peak	WK	T	0.771	1254 (19)
3

Note: Daily peak and off-peak reading count in parentheses

From the raw data in Table 5-2, daily energy readings for weekday peak and off-peak as well as weekend off-peak could be calculated by multiplying the average demand reading for each TOU period by the reading count. The reading count was based on the peak period and off-peak periods defined in the tariff (Table 3-1). The reading count consisted of 2 208 sample hours of which of 330 were weekday peak hours, 1 254 weekday off-peak hours and 624 weekend off-peak hours. Similarly there were 5 daily peak hours for weekdays, 19 daily off-peak hours for weekdays and 48 off-peak hours for weekends. Energy readings were calculated based on the standard formula for electrical energy:

$$\begin{aligned} \text{Energy}_{p,o} &= \text{Average Power}_{p,o} \times \text{time}_{p,o} \\ &= \text{Average Reading}_{p,o} \times \text{Reading Count}_{p,o} \end{aligned} \quad (5-1)$$

where:

p = peak

o = off-peak.

The daily peak and off-peak energy values were determined by multiplying the daily energy count (5 hours for peak and 19 hours for off-peak) by the average demand reading per period (average peak and off-peak, respectively). Weekday and weekend consumption were determined by summing the total weekday use (daily total multiplied by five) as well as the total weekend use (daily weekend use multiplied by two). Customer names were also

replaced by customer numbers to honour certain confidentially agreements. An example of the final customer load dataset that was produced appears in Table 5-3.

Table 5-3: Example of final customer load dataset and fields

Cust_num / observation	CST_GROUP – Control (CON) or Treatment (TOU)	Sitecode – Tableview(T) or Sandton (S)	Daily peak energy (kWh) - K_p	Daily off-peak energy (kWh) - K_o	Daily total energy (kWh)	Weekday total (kWh)	Weekend total (kWh)
1	CON	T	11.50	20.00	31.50	157.50	80.05
2	TOU	T	15	25	40	200	90
...

A separate spreadsheet was generated for the Sandton and Tableview customers. The complete datasets are illustrated in Appendix E1 and E2, respectively. For the Sandton panel data set there were 74 observations, of which 38 were control customers and 36 were treatment customers. For the Tableview panel data set there were 93 observations, of which 48 were control customers and 46 were treatment customers.

5.4 TOU electricity prices

The peak and off-peak prices were also extracted from the database based on the tariff prices for the 2001 pilot period. The prices for the treatment customers were 70c/kWh during peak times and 17.12c/kWh during off-peak times. Control customers were subject to the standard flat rate charge of 25c/kWh. These prices were applied for both the Sandton and Tableview areas. The TOU prices are summarised in the Table 5-4:

Table 5-4: TOU energy rate prices for HomeFlex

Time of use	2 part TOU (T2) - Treatment customers			
	Weekday	Weekend	Price (cents/kWh)	Hours
00:00 to 06:00	off-peak	off-peak	17.12	6
06:00 to 07:00	off-peak	off-peak	17.12	1
07:00 to 10:00	peak	off-peak	70.06	3
10:00 to 18:00	off-peak	off-peak	17.12	8
18:00 to 20:00	peak	off-peak	70.06	2
20:00 to 22:00	off-peak	off-peak	17.12	2
22:00 to 00:00	off-peak	off-peak	17.12	2

Table 5.5 summarises the Caves and Christensen (1984b) notation for peak price and off-peak prices based on the values obtained from the database. The peak to off-peak price ratio was thus 4.1:1.

Table 5-5: TOU energy rate prices – econometric notation

Experiment	Peak period price (P_p)	Off-peak period price (P_o)	Price ratio (P_p/P_o)
Sandton treatment	70.06c/kWh	17.12c/kWh	4.092
Tableview treatment	70.06c/kWh	17.12c/kWh	4.092
All control customers	25c/kWh	25c/kWh	1.000

5.5 Customer characteristics

This data is usually gathered through surveys conducted either prior to or during the experiment. Information for each control and treatment customer is gathered on the following typical variables:

- Appliance ownership.
- Appliance energy ratings and use patterns.
- Socio-demographic information such as age of household head, the number of persons in the household, income levels, etc.

No survey data for the HomeFlex pilot project was available for this study. It was not certain if this data was not captured originally or was simply withheld. Important variables such as appliance ownership for each customer in the experiment could therefore not be determined. The analysis that includes appliance ownership as a primary variable is thus excluded from this analysis. This is a limitation of this study but is left for future research.

A variable representative of a customer's consumption level was this substituted for the traditional conditioning variable. This consumption level variable was identified by analysing the daily and monthly averages for both control and treatment customers in the experiment (Table 5-6). The daily averages for Sandton treatment and control customers were 71.7kWh/day and 76.82kWh/day, respectively. Lower daily averages were obtained for Tableview customers at 34.94kWh/day and 35.72kWh/day for treatment and control customers, respectively.

Table 5-6: HomeFlex customers' consumption averages (Winter 2001)

Experiment	Group	Daily peak kWh (Kp)	Daily off-peak kWh (Ko)	Daily total	Monthly average
Sandton	Treatment	15.05	56.65	71.70	2151.01
	Control	22.31	54.51	76.82	2304.68
Tableview	Treatment	7.76	27.18	34.94	1048.17
	Control	10.68	25.04	35.72	1071.48

Based on this, a range consumption variable represented by D_{consi} was defined. This is a binary variable that is equal to '1' if a customer's consumption level falls within the specified range, otherwise it is '0'. This is described in Table 5-7. The variable was determined by cross referencing against each control and treatment customer's monthly / daily consumption totals in the database.

Table 5-7: Definition of range consumption variable

Monthly consumption (kWh)	Daily consumption (kWh)	$D_{consLOW}$	$D_{consMED}$	$D_{consHIGH}$
		0 – 1000	0 - 32.88	1
1001 – 2001	32.91 – 65.75	0	1	0
2001 – 5000	65.79 – 164.38	0	0	1

These ranges were chosen to coincide with the 1 000kWh per month consumption threshold specified in the Electricity Regulation Act (4/2006) (DME, 2008). Schedule 2(c) of the Act states that all end users or customers consuming 1 000kWh and above must have a smart system installed and should be on a TOU tariff by 2012.

The primary purpose of specifying a variable below the consumption threshold of 1 000kWh/month, i.e., $D_{consLOW}$, as well as a variable above 1 000kWh/month, i.e., $D_{consMED}$ and $D_{consHIGH}$, was to test the relationship of consumption levels with customers' response to time-varying prices. Thus Hypothesis 1, which states that high-use residential customers will respond more significantly to TOU pricing than low-use customers, could be tested. If higher estimates are obtained when the $D_{consMED}$ and $D_{consHIGH}$ are included, then one could conclude that customers consuming above 1 000kWh per month may be more responsive to TOU pricing.

5.6 Climate variation data

The second variable to be included is the number of heating degree hours for each experiment. Hourly minimum and maximum temperature data for the winter period of 2001 for each geographic area was obtained from the Eskom weather database. This data was downloaded from weather stations located at OR Tambo International airport for the Sandton area and Cape Town International airport for the Tableview area. This data was then tabulated and the number of peak and off-peak HDHs calculated based on equation (5-2).

First, the difference in hourly temperatures from a base temperature of 16 Degrees Centigrade (°C) was calculated for each hour over the three-month winter period (June 2001 to August 2001). Second, the average peak HDHs and average off-peak HDHs per day were determined. The difference between the average peak HDHs and the average off-peak HDHs yielded the average daily HDH. The difference in HDH between peak and off-peak was taken instead of the ratio because on some days there were no (zero) average peak HDHs (average daily temperature was equal to base temperature of 16°C) and the ratio would have yielded zero values (Faruqui and Sergici, 2009). The data is summarised in Table 5.8 for both the Sandton and Tableview geographic areas.

$$\begin{aligned} \text{HDH} &= \text{HDH}_{\text{peak}} - \text{HDH}_{\text{offpeak}} \\ &= (T_b - T_{\text{ave_peak}}) - (T_b - T_{\text{ave_offpeak}}) \end{aligned} \quad (5-2)$$

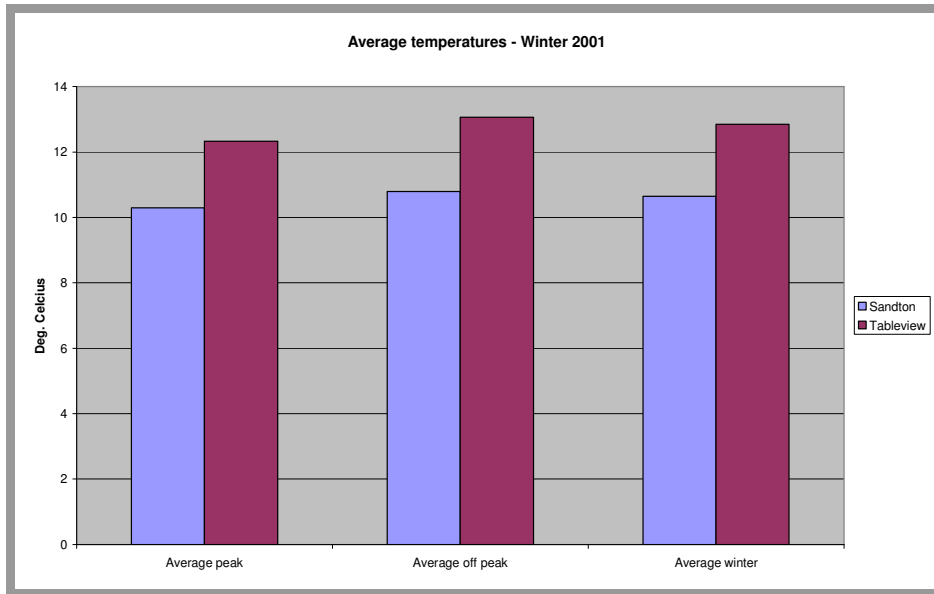
Table 5-8: Average HDH (Winter 2001)

Experiment	Geographic area	Base temp (T _b)	Average peak temp. T _{ave_peak}	Average off-peak temp. T _{ave_offpeak}	Average peak heating degree hours (HDH _{peak})	Average off-peak heating degree hours (HDH _{offpeak})	Average heating degree hours (HDH)
Sandton	Johannesburg	16° C	10.30	10.79	7.99	4.66	3.33
Tableview	Cape Town	16° C	12.33	13.06	5.13	2.63	2.50

Figure 5-6 shows graphically the variation in temperatures over the two geographic areas. The average peak period temperatures for Sandton and Tableview were 10.3°C and 12.3°C, respectively. The average off-peak temperatures were 10.79°C and 13.06°C, respectively.

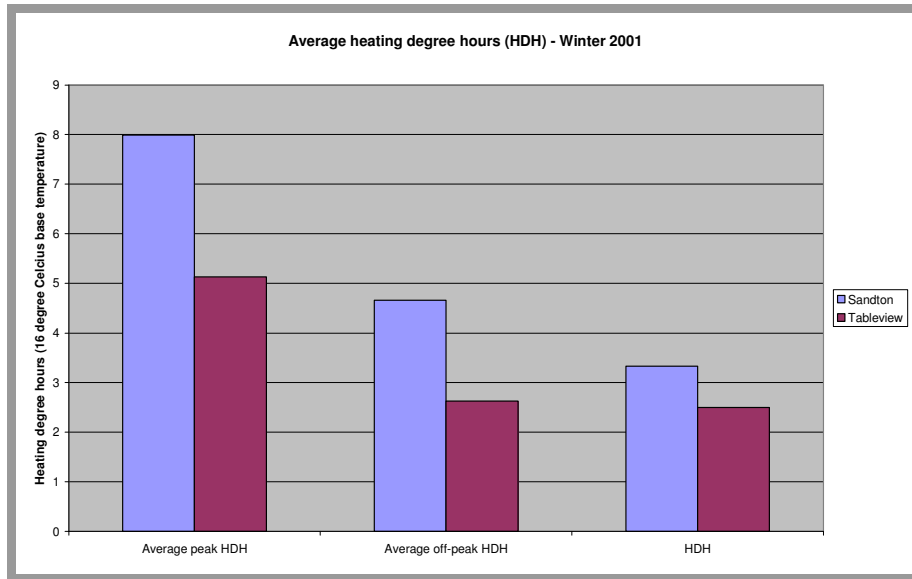
Over the sample period taken for analysis the average winter temperatures were 10.65°C and 12.85°C, respectively.

Figure 5-1: Average temperatures (Winter 2001)



There were 3.33 HDHs for Sandton and 2.5 HDHs for Tableview as seen in Figure 5-7. This is as was expected, as the average winter temperature for Sandton is lower than that for Tableview. For example, the 3.33 HDHs for Sandton implies that for the average winter day, 3.33 average hours of space heating would be required in order to maintain a comfort level of 16°C across peak and off-peak periods.

Figure 5-2: Average HDDs (Winter 2001)



5.7 Summary of econometric notations

A summary of the data parameters and related econometric notation is to be found in the following table. These are the consumption and price/cost ratios used in the econometric notation.

Table 5-9: Data parameters for econometric analysis

Analysis stage	Use ratio	Caves and Christensen notation	Price ratio	Caves and Christensen notation
Stage 1	Peak kWh / off-peak kWh	K_p/K_o	Peak price / off-peak price	P_p/P_o
Stage 2	Weekday total kWh / Weekend total kWh	E_w/E_h	Weekday cost / Weekend costs	P_w/P_h
Stage 3	Electricity expenditure / Expenditure on other goods	E_t/E_g	Electricity costs / Costs of other goods	P_t/P_g

5.8 Conclusion

The econometric analysis of the impact TOU pricing is done with panel datasets. These are datasets that consist of cross-sectional observations of each control and treatment customer in the pricing experiment. An 'experiment' refers to a particular geographic area being observed and in the case of the HomeFlex project these are Sandton and Tableview. The cross-sectional observations in each experiment are obtained from four key dataset parameters:

- 1) Customer load data for peak and off-peak period energy consumption (kWh).
- 2) Electricity prices that were in effect for the experimental tariff. For treatment customers this would typically be peak and off-peak period prices (c/kWh) and for control customers this would be the standard flat rate charge (c/kWh).
- 3) Data for customer characteristics obtained from surveys conducted by the utility. These would include socio-demographics such as appliance ownership, household income, number of residents per household, etc.
- 4) Climate data such as the minimum and maximum temperatures for the geographic areas in the experiment/s.

The customer load data and electricity tariff prices were obtained from the HomeFlex database. This yielded an observation for each control and treatment customer in both the Sandton and Tableview areas. There were 74 observations for Sandton and 93 observations for Tableview.

No socio-demographic data was available and instead a variable representing each customer's consumption level (kWh/month) was used as a binary variable in the OLS regression. This variable was determined by cross-referencing against each customer's daily / monthly average for the winter period of 2001. The rationale for choosing the variable was based on the requirements specified in the Electricity Regulation Act (4/2006) (DME, 2008). Furthermore, the monthly average (and hence daily average) consumption data, obtained from conventional energy meters for each customer, was readily available from utility databases.

The climate data was obtained from weather stations located in close proximity to each of the Sandton and Tableview geographic areas. From this the daily HDHs per geographic area were determined. There were an average of 3.33 HDHs for the relatively cold area of Sandton and an average of 2.5 HDH for the (relatively) warmer Tableview area. There was

thus a temperature differential between these two geographically separated areas, as would be expected.

CHAPTER SIX : ANALYSIS AND DISCUSSION OF RESULTS

The previous chapter identified the data and parameters that are required for an econometric assessment of TOU pricing. This chapter proceeds with the analysis of the data that was identified and a discussion of the results.

Section 6.1 presents a brief introduction to the chapter and **Section 6.2** identifies the tools and statistical methods used in this analysis. **Section 6.3** briefly explains the approach taken to test the hypothesis. **Section 6.4** presents the results obtained for stage 1, with and without conditioning variables. **Section 6.5** presents the results obtained for stage 2, with and without conditioning variables. **Sections 6.7** and **6.8** show how the results can be interpreted and used, respectively. **Section 6.9** makes a comparison to other studies. **Sections 6.10** and **6.11** illustrate the impact of this form of pricing on both the utility and the customer. **Section 6.12** concludes this chapter.

6.1 Introduction

The Caves and Christensen approach (1984a) analysed the effect of TOU pricing by separating the analysis into three stages. Stage 1 analyses the ratio of peak to off-peak consumption as a function of peak to off-peak prices and conditioning variables. Stage 2 analyses the ratio of weekday consumption to weekend consumption as a function of peak to off-peak prices and conditioning variables. Stage 3 of the model analyses the ratio of electricity expenditure to the expenditure on other goods and is a function of household income. ‘Conditioning variables’ are those variables that could be expected to determine the extent of customers’ response to TOU pricing. These include appliance ownership levels, income per household as well as other socio-demographic factors. The CES functional form was chosen as this represents the full range of substitution possibilities between consumption periods.

6.2 Techniques used in the analysis

The substitution equations (4-27, 4-28, and 4-39) identified in section 4.3 (Chapter 4) can be estimated using the generally acceptable method of OLS regression. This regression method yields unbiased parameter estimates with general assumptions about the statistical distribution of the error term. This assumption requires that the error term be independently

and identically distributed according to normal distribution with a zero mean and constant variance. The Least Squares method is a regression technique used for fitting a straight line through a set of data points such that the sum of the squared vertical distances from the observed points to the fitted line is minimised. This is a general approach to fitting a model to the observed data. The model is specified by an equation with free parameters and the values of the model parameters are chosen to minimise the sum of the squared deviations of the data from the values predicted by the model.

The estimates are evaluated for statistical significance by observing the t-statistic as well as the p-values of the coefficients. The confidence level is at 95% and estimates below or above this confidence level are indicated as such.

6.3 Testing the hypothesis

In order to test the hypothesis that states that the price ratio in TOU pricing has a greater effect on the ratio of consumption than any other factors, the following approach to the analysis is taken:

- a) Input the data variables into the model.
- b) Run the regression.
- c) Correct the data if needed by removing outliers.
- d) Re-run the model if required.
- e) Determine the coefficients for each of the independent variable/s for each experiment, i.e., the daily peak to off-peak price coefficient, as well as the coefficients for the conditioning variables.
- f) Determine if the coefficients are statistically significant.
- g) Repeat for stage 2 and 3.
- h) Finalise the estimates.
- i) Accept or reject the hypothesis by observing the estimates.

6.4 Estimates of stage 1

The stage 1 analysis is approached by first obtaining baseline estimates, i.e., subjecting the coefficients of the conditioning variables to zero. Thereafter the conditioning variables are included and a comparison made to the baseline estimates.

6.4.1 Estimates obtained with no conditioning variables

The Stage 1 baseline estimates are obtained by initially subjecting the γ and δ coefficients to zero in equation (4-27). This implies that the effect of weather variations have no effects on the elasticities of substitution which is an oversimplification but serves as a basis by which the full analysis estimates can be compared against. This reduces equation (4-27) to:

$$\ln(K_p / K_o) = \alpha_{i_i} - \beta_{i_i} \ln(P_p / P_o) \quad (6-1)$$

The α_{i_i} (intercept) and β_{i_k} (slope) terms are then determined using OLS regression where $k=S$ for Sandton customers and $k=T$ for Tableview customers. The parameters of interest are the β_{i_k} coefficient terms, which are the elasticities of substitution for each experiment. For Sandton, the regression produces an intercept term $\alpha_I = -0.887$ and a slope term $-\beta_I = -0.384$, which are statistically significant at the 95% confidence interval. For Tableview customers the intercept term is $\alpha_I = -0.865$ and the slope term $-\beta_I = -0.339$ and the results are also statistically significant. One can conclude that the high t-stat values obtained indicate a significant statistical relationship between the consumption ratio $\ln(K_p/K_o)$ and the price ratio $\ln(P_p/P_o)$. Thus the β_I terms are the elasticity of substitution baseline estimates when no conditioning variables are included in the regression.

The results are summarised in Table 6-1 for both Tableview and Sandton customers for the winter period of 2001 and serve as a baseline estimate prior to any conditioning variables included in the regression.

Table 6-1: Stage 1 estimate with no conditioning variables

Experiment	Observations	Estimated parameter	Estimate	Standard error	t-stat	p value	R ²
Sandton	74	β_{IS}	0.384	0.28	8.18	<0.0001	0.59
Tableview	93	β_{IT}	0.339	0.04	7.47	<0.0001	0.38

6.4.2 Estimates obtained with conditioning variables

Recall that the two conditioning variables identified in Chapter 4 (Data for Econometric Analysis) are:

- 1) A range consumption variable, specified as D_{consi} , which is a variable representing a customer's average daily energy consumption. This is a binary value ('1' if within range, otherwise '0') that is determined by cross-referencing each customer's daily energy

consumption in the datasets. Where i =low range (0-32.88kWh/day), medium range (32.91-65.75kWh/day) and high range (65.79 to 164.38kWh/day).

- 2) A climate variation variable, specified as D_{HDH} , which is an integer representing the average number of daily HDHs for the analysis period (winter months of 2001). This was determined to be 3.33 HDHs for Sandton and 2.5 HDHs for Tableview (see Table 5-8, Chapter 5).

6.4.2.1 Daily range consumption conditioning variables

The range consumption variable, D_{consi} , is then entered separately in the regression for equation (4-27). The γ_i coefficient represents the effect of the conditioning variables on the consumption ratio $\ln(K_p/K_o)$ when the price ratio $\ln(P_p/P_o)$ is zero, i.e., $P_p = P_o$. The β_{1k} term is the coefficient of the price ratio $\ln(P_p/P_o)$ and represents the elasticity of substitution between peak and off-peak consumption. The δ_{ik} coefficient represents the effect of the conditioning variables on the elasticity of substitution. None of the α_i coefficients (intercept terms) and γ_i coefficients are reported on from this point forward since the primary variables of interest are the β_{1k} and δ_{ik} coefficients.

Table 6-2 summarises the estimates when $D_{consLOW}$ (monthly consumption less than 1 000kWh/month) is included as a conditioning variable. The estimates decrease when compared to the baseline estimates in Table 6-1. This is as expected as only 9 Sandton customers' daily consumption fell in the low range (12%); 39 (42%) Tableview customers' consumption fell in the low range. The β_{1k} coefficients are statistically significant for both experiments at the 95% confidence interval. The δ_{ik} coefficients for both experiments, however, are not statistically significant at the 95% confidence interval, as indicated by the p-values obtained. There is less than 95% probability that the $D_{consLOW}$ independent variable (low range consumption) has an effect on the dependent variable ($\ln(K_p/K_o)$). The negative values obtained for this coefficient indicates a decrease in the elasticity of substitution as can be seen in the change in β_{1k} for both experiments.

Table 6-2: Stage 1 estimate with low range consumption as conditioning variable

Experiment	Observations	Estimated parameter	Estimate	Standard error	t-stat	p value	R ²
Sandton	74	β_{IS}	0.347	0.04	7.79	<0.0001	0.60
		$\delta_{consLOWS}$	-0.184	0.13	2.70	0.0621	
Tableview	93	β_{IT}	0.254	0.06	3.94	0.0002	0.41
		$\delta_{consLOWT}$	-0.164	0.09	1.83	0.0713	

When the $D_{consMED}$ variable (consumption greater than 1 000kWh/month and less than 2 000kWh/month) is included, the β_{ik} estimates increase slightly for both Sandton and Tableview, as shown in Table 6-3, and are statistically significant at the 95% confidence interval. Again the δ_{ik} coefficients are not statistically significant at the 95% confidence interval for both experiments. The higher elasticity of substitution estimates for Tableview can be explained by the higher concentration of medium range customers in this experiment (52%) as compared to the number in Sandton (35%). None of the δ_{ik} coefficients are statistically significant at the 95% confidence interval, for both experiments, as indicated by the p-values obtained.

Table 6-3: Stage 1 estimate with mid range consumption as conditioning variable

Experiment	Observations	Estimated parameter	Estimate	Standard error	t-stat	p value	R ²
Sandton	74	β_{IS}	0.387	0.06	6.47	<0.0001	0.48
		$\delta_{consMEDS}$	0.016	0.10	0.15	0.3925	
Tableview	93	β_{IT}	0.391	0.06	6.56	<0.0001	0.39
		$\delta_{consMEDT}$	0.125	0.09	1.35	0.3797	

Finally, when the $D_{consHIGH}$ variable is included there is a marked increase in the estimates from the baseline values for the elasticity of substitution. The β_{ik} coefficients obtained are statistically significant for both Sandton and Tableview customers as shown in Table 6-4. The δ_{ik} coefficients, however, are not statistically significant at the 95% confidence interval. The $D_{consHIGH}$ (high range) variable, as defined, does not have an effect on the variation in the dependent variable. The higher elasticity of substitution estimates obtained for Sandton customers are probably due to the higher concentration of high range consumption customers in this experiment (53%) as compared to Tableview (6%).

Table 6-4: Stage 1 estimate with high range consumption as conditioning variable

Experiment	Observations	Estimated parameter	Estimate	Standard error	t-stat	p value	R ²
Sandton	74	β_{1S}	0.429	0.07	6.47	<0.0001	0.53
		$\delta_{\text{consHIGHHS}}$	0.120	0.09	1.32	0.280	
Tableview	93	β_{1T}	0.351	0.05	7.56	<0.0001	0.41
		$\delta_{\text{consHIGHT}}$	0.067	0.19	0.88	0.379	

6.4.2.2 Climate variation conditioning variable

The effects of weather conditions on the estimates are determined by first excluding D_{HDH} as a conditioning variable in order to determine a baseline estimate. This is done by combining both Sandton and Tableview panel data in order to determine if daily HDHs affect the daily peak to off-peak consumption ratio, and if they are statistically significant as an independent variable in the regression. Table 6-5 summarizes the estimates when HDH is not included as a conditioning variable. Once more there is a significant relationship between consumption and price. The β_{IS+T} coefficient is statistically significant at the 95% confidence interval.

Table 6-5: Stage 1 estimates with combined data for geographic areas with no conditioning variables

Experiment	Observations	Estimated parameter	Estimate	Standard error	t-stat	p value	R ²
Sandton and Tableview	167	β_{IS+T}	0.346	0.03	10.97	<0.0001	0.42

Including the D_{HDH} as a independent variable increases the elasticity of substitution and the β_{IS+T} coefficient is statistically significant at the 95% confidence interval. The δ_{HDH} coefficient, however, is not statistically significant as shown in Table 6-6.

Table 6-6: Stage 1 estimate with combined data for geographic areas with HDH as a conditioning variable

Experiment	Observations	Estimated parameter	Estimate	Standard error	t-stat	p value	R ²
Sandton and Tableview	167	β_{IS+T}	0.342	0.087	3.94	0.0001	0.43
		δ_{HDH}	0.046	0.136	0.68	0.7345	

It is plausible to deduce that the variation in daily peak to off-peak temperatures does not affect the elasticity of substitution estimates as much as the price interaction does. This is to be expected as none of the load shedding enabling technologies used in the HomeFlex pilot

project was temperature related, i.e., no space heating loads were disconnected during the peak and off-peak periods. Furthermore, it is evident that no further load shifting was done by customers in relation to daily temperature variations.

6.4.3 Summary of stage 1 estimates

The effect of the price ratio as an independent variable is thus more significant than any of the conditioning variables used, i.e., daily consumption levels and climate effects, as can be seen in the summarised estimates provided in Table 6-7. The lower R^2 values obtained for Tableview indicate that the model provides a poor 'goodness of fit' and that less than 40% of the variation in peak to off-peak consumption ratio can be explained by the range consumption variable. A higher percentage of the variation can be explained by the Sandton estimates as can be seen by the higher R^2 values obtained for this area. The climate variation variable also shows a poor 'goodness of fit' as can be seen by the low R^2 values obtained when comparing this effect across the Sandton and Tableview areas.

However all of the β_{ik} coefficients for stage 1 have the expected positive sign (substitutes) and are statistically significant at the 95% confidence as seen by the high t-stat and lower p-values. The conditioning variables alter the magnitude of the β_{ik} coefficients but none of the δ_{ik} coefficients are statistically significant at the 95% confidence interval, as seen by the high p-values and low t-stat values.

Table 6-7: Summary of Stage 1 estimates

Experiment	Observations	Estimated parameter	Estimate	Standard error	t-stat	p value	R ²
Sandton	74	β_{IS}	0.384 ^a	0.28	8.18	<0.0001	0.59
		β_{IS}	0.347 ^a	0.04	7.79	<0.0001	0.60
		$\delta_{consLOWS}$	-0.184	0.13	2.70	0.0621	
		β_{IS}	0.387 ^a	0.06	6.47	<0.0001	0.48
		$\delta_{consMEDS}$	0.016	0.10	0.15	0.3925	
		β_{IS}	0.429 ^a	0.07	6.47	<0.0001	0.53
		$\delta_{consHIGHS}$	0.120	0.09	1.32	0.280	
Tableview	93	β_{IT}	0.339 ^a	0.04	7.47	<0.0001	0.38
		β_{IT}	0.254 ^a	0.06	3.94	0.0002	0.41
		$\delta_{consLOWT}$	-0.164	0.09	1.83	0.0713	
		β_{IT}	0.391 ^a	0.06	6.56	<0.0001	0.39
		$\delta_{consMEDT}$	0.125	0.09	1.35	0.3797	
		β_{IT}	0.351 ^a	0.05	7.56	<0.0001	0.41
		$\delta_{consHIGHT}$	0.067	0.19	0.88	0.379	
Sandton and Tableview	167	β_{IS+T}	0.346 ^a	0.03	10.97	<0.0001	0.42
		β_{IS+T}	0.342 ^a	0.09	3.94	0.0001	0.43
		δ_{HDH}	0.046	0.14	0.68	0.7345	

^a Statistically different from 0 at a 5% level

The effect of the conditioning variables at stage 1 was shown to be statistically insignificant and can thus be ignored for all intents and purposes. The baseline estimates with no conditioning variables can be substituted in equation (6-1). The model for Sandton customers, that relates the ratio of peak and off-peak consumption to peak and off-peak prices, is thus:

$$\begin{aligned}
 \ln(K_p/K_o) &= -0.887 - (-0.384) \cdot \ln(P_p/P_o) \\
 &= -0.887 + 0.384 \cdot \ln(P_p/P_o)
 \end{aligned}
 \tag{6-2}$$

A similar model can be constructed by substituting the estimates obtained for Tableview customers.

$$\ln(K_p/K_o) = -0.865 + 0.339 \cdot \ln(P_p/P_o) \quad (6-3)$$

6.5 Estimates of stage 2

A similar approach to stage 1 is taken for stage 2 by first obtaining the baseline estimates, i.e., subjecting the coefficients of the conditioning variables to zero. Thereafter the conditioning variables are included and a comparison made to the baseline estimates.

6.5.1 Estimates obtained with no conditioning variables

This stage represents the shifting of consumption from weekdays to weekends by customers in response to TOU tariffs. The analysis is first done with no conditioning variables, i.e., the ratio of weekday to weekend consumption $\ln(E_w/E_h)$ is the dependent variable and the ratio of weekday to weekend prices $\ln(P_w/P_h)$ is the independent variable in the linear regression. Equation (4-28) thus reduces to:

$$\ln(E_w/E_h) = \alpha_2 + (1 - \beta_2) \cdot \ln(P_w/P_h) \quad (6-4)$$

Table 6-8: Stage 2 estimate with no conditioning variables

Experiment	Observations	Estimated parameter	Estimate	Standard error	t-stat	p value	R ²
Sandton	74	β_{2S}	0.518	0.04	9.82	<0.0001	0.57
Tableview	93	β_{2T}	0.457	0.04	13.16	<0.0001	0.66

For Sandton customers, the regression produces a baseline intercept term $\alpha_2 = 0.219$ and a slope term $\beta_2 = 0.518$, which are statistically significant at the 95% confidence interval. For Tableview customers the intercept term is $\alpha_2 = 0.107$ and the slope term $\beta_2 = 0.457$, these are also statistically significant. The higher R² values obtained in this stage indicate that a larger percentage of the variation in the ratio of weekday to weekend consumption (dependent variable) can be explained by a variation in the ratio of weekday to weekend prices (independent variable). This is further substantiated by the higher t-stat values obtained.

These elasticity of substitution estimates obtained for both Sandton and Tableview customers represent the customers' ability to substitute weekday consumption for weekend consumption, i.e., they are able to shift some of their normal weekday consumption to the weekend due to the lower weekend prices. Significant β_{2k} coefficients suggest that, for both experiments, customers substitute a portion of weekday consumption for weekend consumption. This is substantiated by the engineering approach results obtained by Dekenah et al. (2004) that showed higher weekend consumption levels by the treatment group when compared to the control group.

6.5.2 Estimates obtained with conditioning variables

Following the same approach that was taken in stage 1 of the analysis, and for consistency in using the conditioning variables, the variable D_{cons} is entered in the regression for equation (4-28) separately for low, medium and high consumption. Each variable is a binary value in relation to a customer's daily energy consumption.

The elasticity of substitution estimates decrease when $D_{consLOW}$ is included as a conditioning variable as compared to the baseline estimates. At least 70% of the variation in $\ln(E_w/E_h)$ can be accounted for in the variation in $\ln(P_w/P_h)$ as also indicated by the higher t-stat values obtained. One can conclude that low-range consumption customers would substitute less weekday for weekend use. The estimates are summarised in Table 6-7.

Table 6-7: Stage 2 estimate with low-range consumption as conditioning variable

Experiment	Observations	Estimated parameter	Estimate	Standard error	t-stat	p value	R ²
Sandton	74	β_{2S}	0.482	0.04	9.17	<0.0001	0.70
		$\delta_{consLOWS}$	0.287	0.18	1.63	0.1002	
Tableview	93	β_{2T}	0.380	0.06	9.86	<0.0001	0.67
		$\delta_{consLOWT}$	0.209	0.12	1.66	0.1014	

When $D_{consMED}$ is included as a conditioning variable the estimate obtained for Sandton customers is similar to that obtained in the baseline estimate and is statistically significant. Larger estimates are obtained for Tableview customers than Sandton customers as shown in Table 6-8.

Table 6-8: Stage 2 estimate with mid-range consumption as conditioning variable

Experiment	Observations	Estimated parameter	Estimate	Standard error	t-stat	p value	R ²
Sandton	74	β_{2S}	0.581	0.05	8.33	<0.0001	0.58
		$\delta_{consMEDS}$	0.104	0.167	0.63	0.5312	
Tableview	93	β_{2T}	0.530	0.05	8.92	<0.0001	0.67
		$\delta_{consMEDT}$	0.234	0.13	-1.85	0.06	

Finally the $D_{consHIGH}$ variable is included as a conditioning variable. The elasticity of substitution further decreases and is statistically significant at the 95% confidence level as shown in Table 6-9.

Table 6-9: Stage 2 estimate with high-range consumption as conditioning variable

Experiment	Observations	Estimated parameter	Estimate	Standard error	t-stat	p value	R ²
Sandton	74	β_{1S}	0.626	0.05	5.54	<0.0001	0.60
		$\delta_{consHIGHHS}$	0.269	0.16	-1.68	0.09	
Tableview	93	β_{2T}	0.553	0.04	12.93	<0.0001	0.66
		$\delta_{consHIGHHT}$	0.370	0.51	0.72	0.72	

6.5.3 Summary of stage 2 estimates

The elasticity of substitution, between weekday and weekend consumption, increases for high consumption customers. The estimates for the β_{2k} coefficients are statistically significant. Higher R² values obtained here indicate a better coefficient of determination, i.e., the model explains at least 60% of variation in weekday to weekend consumption by the range consumption variable. Thus high-consumption customers are able to ‘forego’ some of their normal weekday consumption for weekend consumption, due to the difference in weekday and weekend prices, and are more price-elastic in this regard. Therefore the effect of the weekday to weekend price ratio is statistically significant at the 95% confidence interval.

Table 6-10: Summary of stage 2 estimates

Experiment	Observations	Estimated parameter	Estimate	Standard error	t-stat	p value	R ²
Sandton	74	β_{2S}	0.518 ^a	0.04	9.82	<0.0001	0.57
		β_{2S}	0.482 ^a	0.04	9.17	<0.0001	0.70
		$\delta_{consLOWS}$	0.287	0.18	1.63	0.1002	
		β_{2S}	0.581 ^a	0.05	8.33	<0.0001	0.58
		$\delta_{consMEDS}$	0.104	0.167	0.63	0.5312	
Tableview	93	β_{1S}	0.626 ^a	0.05	5.54	<0.0001	0.60
		$\delta_{consHIGHS}$	0.269	0.16	-1.68	0.09	
		β_{2T}	0.457 ^a	0.04	13.16	<0.0001	0.66
		β_{2T}	0.380 ^a	0.06	9.86	<0.0001	0.67
		$\delta_{consLOWT}$	0.209	0.12	1.66	0.1014	
Tableview	93	β_{2T}	0.530 ^a	0.05	8.92	<0.0001	0.67
		$\delta_{consMEDT}$	0.234	0.13	-1.85	0.06	
		β_{2T}	0.553 ^a	0.04	12.93	<0.0001	0.66
		$\delta_{consHIGHT}$	0.370	0.51	0.72	0.72	

^a Statistically different from 0 at a 5% level

The effect of the conditioning variables at stage 2 was shown to be statistically insignificant. The baseline estimates with no conditioning variables can be substituted in equation (6-4). The model for Sandton customers, that relates the ratio of weekday to weekend consumption and weekday to weekend prices, is thus:

$$\ln(E_w/E_h) = 0.219 + 0.518 \cdot (P_w/P_h) \quad (6-5)$$

A similar model can be constructed by substituting the estimates obtained for Tableview customers.

$$\ln(K_p/K_o) = 0.107 + 0.457 \cdot \ln((P_w/P_h)) \quad (6-6)$$

6.6 Estimates of stage 3

No estimates of stage 3 can be performed due to the lack of survey data available for individual customer income levels. Any assumptions on customer income levels, based on the LSM index (Appendix B) for example, may have yielded inaccurate results as this scale is too large and the exact LSM level of each customer in the experiment was not available. Excluding this stage of the analysis is a limitation of this study and it is suggested that future research is done concerning stage 3.

6.7 Interpreting the results

The consumption range variable, when included as an independent variable, did affect the elasticity of substitution estimates but the effect was statistically insignificant. Larger elasticity of substitution estimates were obtained for customers in the high-consumption levels (>1 000kWh per month) than for lower consumption levels (<1 000kWh per month). This is to be expected as high-consumption customers would typically possess a greater level of energy-intensive appliances and thus be more price sensitive, all else being equal.

A larger range of appliances can also contribute to a customer's ability to substitute off-peak energy for peak energy than could be expected from a customer without a full range of appliances. A customer possessing both an electric heater and a gas heater, for example, may switch off the electric heater during peak times and switch on the gas heater for space heating purposes. A customer with only an electric heater may not be able to react in the same fashion, when faced with TOU pricing, in order to maintain the same comfort level. Similarly customers in the high-consumption range are able to forego some of their weekday use for weekend use to take advantage of lower weekend prices.

The HDH climate variable, when included as an independent variable did not affect the estimates and was statistically insignificant. The variation in the peak to off-peak consumption ratios could not be explained by the variation in peak to off-peak daily temperatures and there was no significant correlation between these variables. The daily variation in temperatures did not affect customers' choices in appliance use for the HomeFlex pilot and this is to be expected as the appliances switched off by the enabling technology were not space heating related.

The price ratio, as an independent variable, was however statistically significant for both experiments as can be seen by the β_i coefficients. Thus, the price ratio is the primary dependent variable accountable for the change in the elasticity of substitution estimates and hence the magnitude of customer response to TOU pricing in the HomeFlex experiment.

In combining the findings for stage 1 and stage 2, it is evident that the price ratio (daily peak to off-peak and weekday to weekend prices) has a greater effect on the elasticity of substitution estimates obtained than do any of the conditioning variables. Thus, the hypothesis, which states that the effect of the price ratio is more significant than that of any of the conditioning variables in determining the magnitude of response by customers to TOU pricing, is proven at the 95% confidence interval.

6.8 Using the model to estimate customer response to TOU pricing

The results obtained by stage 1 and 2 of the model can be used to estimate the average response, by the average customer, in the HomeFlex pilot by using the baseline results obtained in stage 1 and stage 2, i.e., the effect of the price ratio on the consumption ratio as the primary determining factor in TOU response for this pilot project. This is plausible since it has been shown that the effects of the conditioning variables are not statistically significant.

The stage 1 elasticity of substitution estimate obtained for Sandton was 0.384. Thus, there is a 95% probability that a 1% increase in the peak to off-peak price ratio will result in a 0.384% decrease in the ratio of peak to off-peak consumption. Likewise there is a 95% probability that an increase in the peak to off-peak price ratio of 100%, will result in a 38.4% decrease in the peak to off-peak consumption ratio. For the stage 2 estimate of 0.518 one can estimate with a 95% probability that a 1% price differential between weekday and weekend prices will induce a shift in consumption of a further 0.518% from weekdays to weekends. These estimated reductions in peak to off-peak daily, as well as weekly consumption use are applicable to customers with an average monthly consumption of 2151.01kWh/month, all else being equal.

For illustrative purposes, Table 6-11 shows the effect on the consumption ratio for an increase in the price ratio by varying the peak price only.

Table 6-11: Effect on consumption ratio as peak to off-peak price ratio increases

Estimate	Peak price	Off-peak price	Price ratio	Price ratio increase	% change in peak to off-peak consumption ratio
0.384 ¹	70.06c/kWh	17.12c/kWh	4.1/1	1%	0.384%
	105.09c/kWh	17.12c/kWh	6.1/1	50%	19.2%
	140.12c/kWh	17.12c/kWh	8.2/1	100%	38.4%

¹*Sandton estimate used for illustrative purposes. Peak price raised and off-peak price kept constant*

Similarly the elasticity of substitution estimate for Tableview of 0.339 indicates that there is a 95% probability that a 1% increase in the peak to off-peak price ratio will result in a 0.339% reduction in the peak to off-peak consumption ratio. Thus a 100% increase in the price ratio is likely to result in a 33.9% reduction in peak to off-peak period use, with a 95% probability. The shift in weekday to weekend consumption is likely to be 0.457% for a 1% change in weekday and weekend prices. These estimates are applicable to the average customer with an average monthly consumption of 1048kWh/month with all other factors been equal.

6.9 Comparison to other studies

The analysis in this dissertation compares favourably with the work of Caves et al. (1984a) who state that the price differential between peak and off-peak consumption is the main factor that contributes to the response of customers to TOU pricing. Taking appliance ownership levels, customer characteristics and the variation in climate into consideration, they found that these effects are discernable but not as significant as the effect of the price differential. A direct comparison to the elasticity of substitution estimates cannot be made as the experiments were fundamentally different, i.e., length of peak periods, price ratios and sample sizes.

Reiss and White (2005) find lower price elasticities estimates for higher consumption customers. This is somewhat surprising, as one would expect customers with high consumption levels to possess a full range of appliances and hence possess much greater price sensitivity, all other factors been equal. Using the OLS method Reiss and White determined a price elasticity estimate of 0.37 for customers with an annual consumption of less than 4 450kWh/yr and a lower estimate of -0.08 for customers using more than

9 700kWh/yr. They however explicitly account for appliance ownership levels and income in their estimates.

The relationship between consumption levels and the elasticity of substitution are to be found in the work of Aigner and Lillard (1984). They found higher elasticity of substitution estimates for high consumption customers in their 1979 study of TOU pricing for the Southern California Edison Company. Their analysis included eight rates (peak to off-peak price ratios), five consumption groups (kWh/year) as well as three temperature zones. They conclude that high consumption customers have larger elasticity of substitution as these customers have more discretionary possibilities in their use patterns.

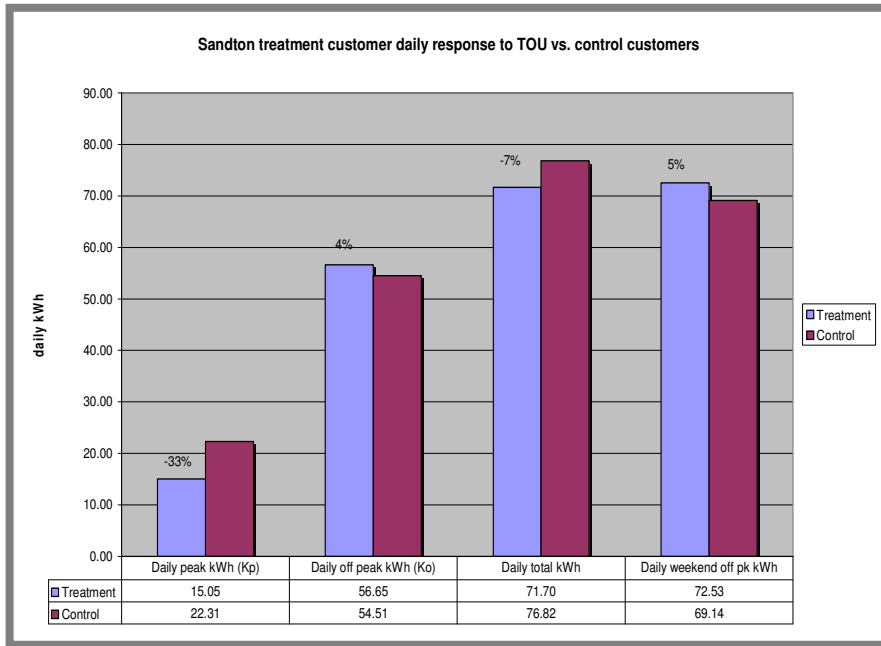
The estimates obtained in this analysis, ranging from 0.339 to 0.384, also compare favourably with those of the GPU pilot in New Jersey (refer to Table 2-2, Chapter 2). This utility offered a residential TOU pilot programme in 1997, which included enabling technologies in the TOU package. Three price tiers were offered (peak, shoulder and off-peak) and a CPP, only effective for a limited number of high-cost summer hours. The programme consisted of a control group and two treatment groups. The CES model used in the analysis yielded an estimate of 0.30, which was larger than that obtained for previous studies in the US, and could be attributed to the enabling technologies made available to customers (Faruqui and Sergici, 2009). It should be remembered that customers in the HomeFlex pilot were also fitted with enabling technologies that automatically switched off appliances (geysers) during peak periods.

6.10 Load curtailment – benefits to the utility

The response of customers in the HomeFlex TOU pricing experiment has some important implications for a utility such as Eskom. In light of the current capacity constraint, the effect of DSM measures such as TOU pricing has significant implications on the optimal utilisation of current and limited resources. In conjunction with the econometric approach, a separate engineering analysis of the data revealed some interesting efficiency improvements that TOU pricing can provide. The data analysis showed that Sandton treatment customers reduced their daily peak consumption by 33% when compared to control customers. Their daily off-peak consumption increased by only 4% and their total daily consumption decreased by 7% when compared to control customers. Some weekday use was shifted to the weekend, but only 5%. Thus, there is a certain level of energy efficiency that took place. Sandton treatment customers also improved their peak to off-peak use ratio by 60% when

compared to control customers. Of importance was also the improvement in the load factor from 72% (control customers) to 91% due to TOU pricing. These results are shown graphically in Figure 6-1.

Figure 6-1: Sandton treatment customers’ daily use shares compared to control customers’ daily use shares



A similar pattern of energy efficiency can be seen for Tableview customers (Figure 6-2). Treatment customers reduced their peak period consumption by 30% when compared to control customers. This group increased their daily off-peak consumption by 8% but decreased their overall daily consumption by 1% when compared to control customers. The peak to off-peak consumption ratio for this group improved by 55% and the weekday to weekend use share increased by 1%. Overall energy efficiency did take place and there was a 24% improvement in load factor.

Figure 6-2: Tableview treatment customers' daily use shares compared to control customers' daily use shares

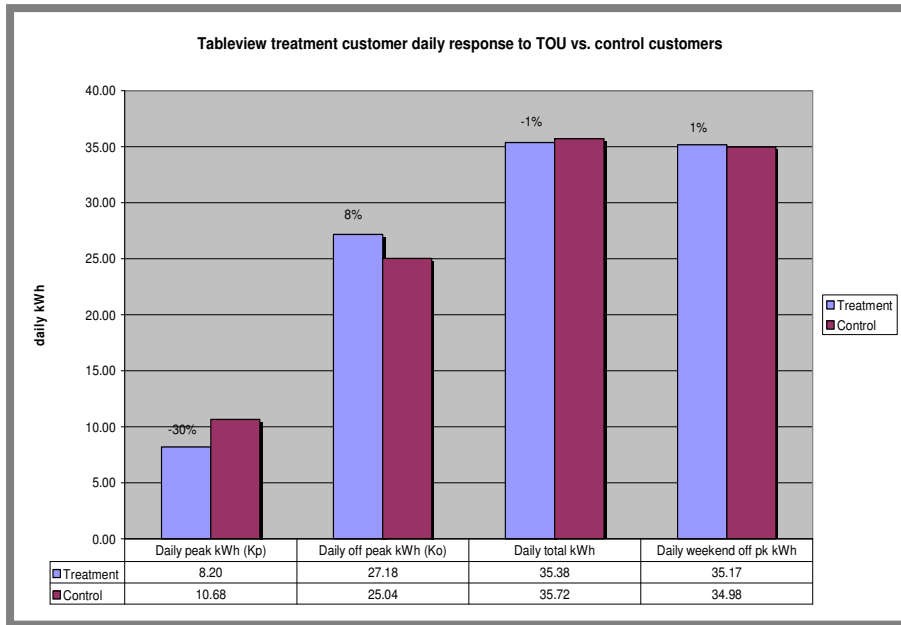
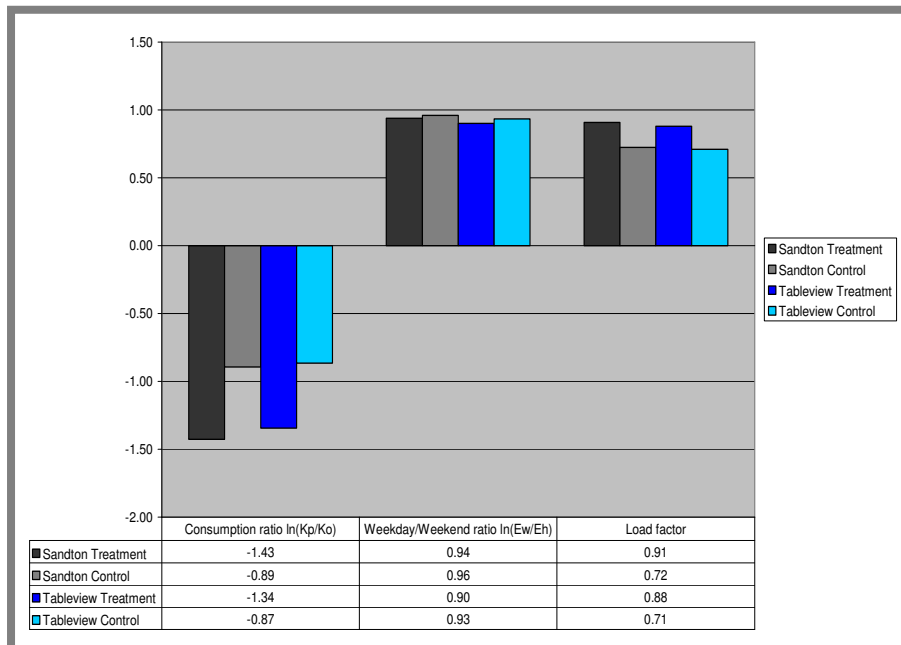


Figure 6-3 illustrates graphically the improvement in the use shares and load factor for each of the two experiments.

Figure 6-3: Sandton and Tableview improvement in use shares and load factor



6.11 Welfare effects – impact on the customer

The effect of TOU pricing on the end customer in terms of an increase or decrease in their monthly bills is referred to as the welfare effect. This is essentially the difference in electricity costs paid by the customer when on TOU rates as compared to electricity costs if the customer was on standard flat rates. In analysing the welfare effects for both Sandton and Tableview, it is evident that for both experiments customers benefit from TOU pricing. For an average winter month during the 2001 sample period, 86% of Sandton customers paid less on TOU rates and 11% paid more. For Tableview, 83% paid less and 17% paid more. The average bill reduction for both groups was 10% (Figures 6-4 and 6-5 for Sandton and Tableview, respectively).

Due to the overall reduction in consumption during the higher-priced hours (weekday peak) and an increase in consumption over the lower-priced hours (weekday off-peak and weekends), there appears to be a reduction in the overall cost to the customer. This, however, has not been verified with any of the Eskom sales data during the pilot project and serves merely to illustrate the impact on the customer due to TOU pricing. One would expect the revenue neutral point to be the same as the average impact on the average customer for both experiments. This can be explained by the fact that the analysis only covered the winter months of 2001. The overall impact of TOU pricing should be revenue neutral to a utility over a complete year else it implies that the tariff has not been properly designed. Further analysis of this is beyond the scope of this dissertation and is left for future research.

Figure 6-4: The welfare impact on Sandton customers

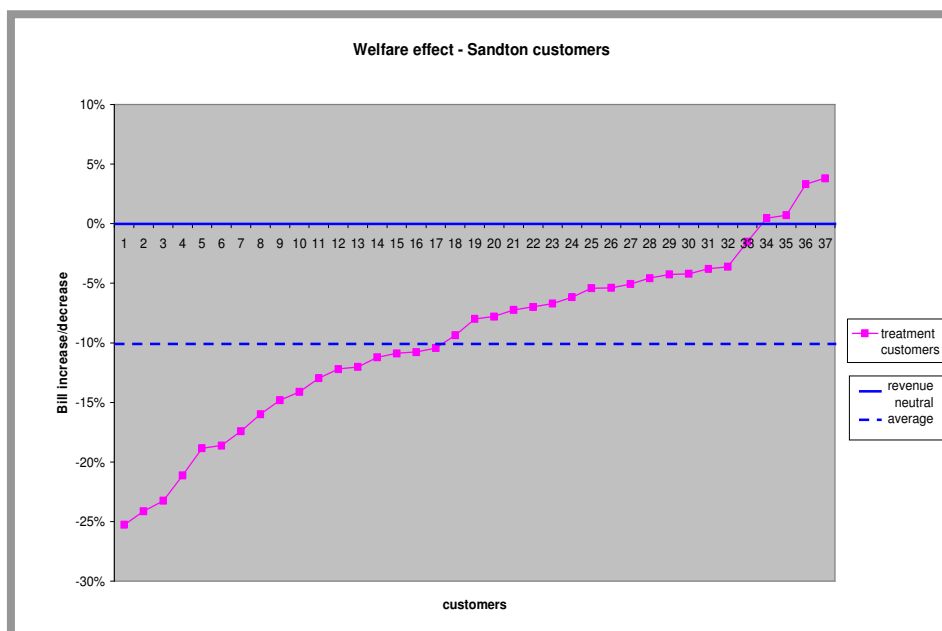
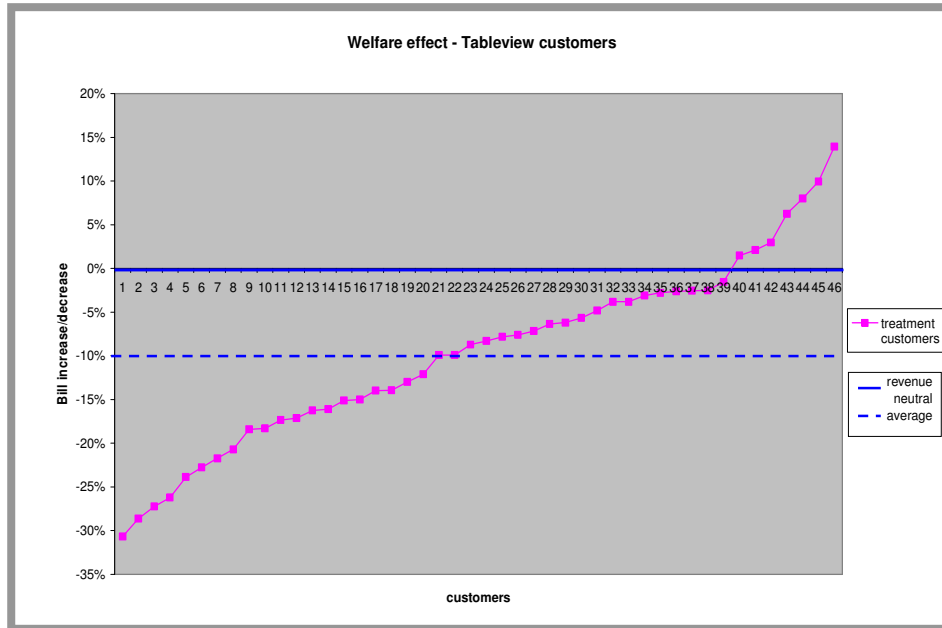


Figure 6-5: The welfare impact on Tableview customers



6.12 Conclusion

This chapter proceeded with the analysis of panel data obtained from the HomeFlex database. The data was analysed using the OLS regression method and the estimates observed for statistical significance. Stage 1 of the econometric analysis involved analysing the effect that the peak to off-peak price ratio had on the peak to off-peak consumption ratio in the HomeFlex pilot. The partial elasticity of substitution estimates obtained for this stage were 0.339 and 0.384 for the Tableview and Sandton customers, respectively, when no conditioning variables were included in the analysis. The estimates all have the expected positive sign and are statistically significant at the 95% confidence interval. When including the range consumption and climate variation variables, the estimates changed, but their effect was statistically insignificant.

Stage 2 of the analysis involved the effect that the weekday to weekend price ratio had on the weekday to weekend consumption ratio. The elasticity of substitution estimates obtained for this stage were 0.457 and 0.518 for the Tableview and Sandton customers, respectively, when none of the conditioning variables were included in the analysis. The estimates were all positive and statistically significant at the 95% confidence interval. Including the range consumption and climate variation variables altered the estimates but their effect was statistically insignificant. The effects of the daily price ratio as well as the weekly price ratio

on the consumption ratio are the primary factors that determined customer response in the HomeFlex pilot project.

Combining the results obtained from stage 1 and stage 2, it was evident that price played a more significant role than any of the fixed effects such as daily consumption and daily temperature variation. The hypothesis that the price ratio has a greater effect than the conditioning variables on the consumption ratio was therefore accepted at the 95% confidence level. Based on this one can deduce that there is a 95% probability that a 1% increase in the HomeFlex price ratio will result in a decrease in the peak to off-peak consumption ratio of 0.384% for the average Sandton customer. This result can be projected to customers with a monthly consumption of 2 151.01kWh/month. The average Tableview customer reduced this ratio by 0.339% and this can be projected to customers with a monthly consumption of 1 048kWh/month, all other factors been equal.

These results compare favourably with other studies found in the literature whereby the price differential was identified to affect the magnitude of customer response to TOU pricing more than the conditioning variables. Exceptions are to be found in the work of Reiss and White (2005) who show a decrease in price elasticity estimates as consumption levels increase. A similar result was found in the GPU pilot in New Jersey done in 1997. The OLS method was used and estimates obtained ranged from 0.339 to 0.384, this was attributed mainly to the enabling technology used in the pilot to assist customers in shedding their appliance loads.

Further analysis revealed that the average Sandton treatment customer reduced their daily peak consumption by 33% when compared to control customers. The treatment customers also increased their off-peak consumption by 4% and decreased their overall daily consumption by 7%. There was a 5% shift of weekday consumption for weekend consumption. The daily load factor of the Sandton treatment group improved by 25%, due to TOU pricing, when compared to the control group's load factor. The average Tableview treatment customer was able to reduce his/her daily peak consumption by 30% when compared to the control customers. The Tableview treatment customers increased their off-peak consumption by 8% and decreased their overall daily consumption by 1%. There was a 24% improvement in the daily load factor by the treatment group. There were improvements in energy efficiency as well as the optimisation of daily consumption across time periods.

The 'welfare effect' analyses the impact that TOU pricing has on the average treatment customer's monthly electricity bill. For the HomeFlex pilot, 86% of Sandton customers are estimated to have paid less on TOU rates and 11% paid more. For Tableview, 83% paid less and 17% paid more. The average bill reduction for both groups was 10%. This was specific to the three winter months of 2001 and was not verified against any sales data.

CHAPTER SEVEN : CONCLUSION AND RECOMMENDATIONS

7.1 Introduction

The objective of this study was to analyse the impact of TOU pricing from an econometric point of view. In doing so the results could be compared to those of other studies by other utilities abroad. A literature review identified a methodology for this approach as well as the generally acceptable measure of TOU pricing response referred to as the elasticity of substitution. The data needed for analysis was identified and subsequently obtained from the database of a recent TOU pilot project conducted by Eskom.

The results from the analysis show that changes in the price ratio are the primary cause of changes in the consumption ratio. Conditioning variables enter the analysis as modifiers to the elasticity of substitution but their effect is insignificant. The hypothesis, which states that the effect of the price ratio on customer response is more significant than the effect of the conditioning variables is not rejected. This study provides a platform for the analysis of future TOU pricing pilot and implementation projects for the utility.

7.2 Limitation of this study

The data used in the analysis was aggregated over the sample period. This method, although simplifying the analysis, results in information been lost, i.e., a customer's use during the peak periods is calculated based on the average maximum use over the sample period. A more accurate method would be to analyze each customer's individual profile data and then summate the consumption per period. This, however, is an intensive exercise and requires multiple datasets to be processed.

Furthermore, the literature identified the factors that influence customers' utilisation decisions when faced with TOU pricing as appliance ownership levels, income levels and other socio-demographic factors. These were not comprehensively included in the analysis as this data was not available. The issue of homotheticity was not considered in this analysis. The implication of homotheticity is that the ratio of peak period to off-peak period consumption is independent of income (Caves et al., 1984a). The homotheticity test was not done due to the lack of data on household income for the HomeFlex project. The assessment

was therefore not complete. This is a limitation of this study and this gap is left for future research.

7.3 Recommendations

In order to provide a complete econometric assessment of TOU pricing using the methodology described in this study, it is recommended that future TOU pilot and implementation projects include a comprehensive dataset. This includes surveys conducted before and after the project that aim to gather information on demographics, income levels and appliance ownership levels per customer.

The peak to off-peak reductions in the HomeFlex pilot could be attributed to a combination of the tariff and the enabling technology that was in place. It is recommended that future sample designs for TOU experimental projects include a treatment group without any enabling technology installed. The aim of this is to identify the response purely due to customer interventions. Furthermore, consumption data for treatment groups should be captured prior to these groups being converted to TOU pricing in order to eliminate the effect of self-selection bias. This process involves analysing the data before and after TOU pricing to compare responses that may not be attributable to the tariff.

A possible criticism of TOU pricing is that it is 'static', i.e., the peak and off-peak rates are fixed. This scheme will provide limited demand response when there are network constraints outside of these periods. Such was the case experienced in SA in January 2008 (Eskom, 2008) where network constraints were experienced outside of peak hours. A more innovative pricing structure is found in CPP. This type of tariff is more dynamic in nature and it is recommended that future time-varying experimental rates include the piloting, data gathering and analysis of CPP tariffs.

7.4 Conclusion

This study shows that TOU pricing can be implemented as an effective DSM strategy in Eskom and other municipalities. The results obtained by this analysis further substantiate the engineering results obtained. There is a benefit to both the utility as well as the customer provided that the tariff is designed with a price ratio significant enough to elicit a response but low enough to ensure customer welfare. The utility benefits are derived by the energy efficiency TOU pricing provides. The reduction in peak period demand and the utilisation of

existing capacity more efficiently further strengthens the case for TOU pricing. The costs of avoided capacity requirements and benefits of energy savings may far outweigh the costs of the required TOU metering infrastructure and other costs associated with the implementation of this tariff. The customer benefits are derived from reduced costs due to a shift in consumption from more expensive time periods to less expensive time periods.

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APPENDICES

Appendix 1A – SA historical loads

Year	Energy Demand (GWh)	Maximum Demand (MW)	Energy Growth Rate	Maximum Demand Growth Rate	Load Factor
1995	163 140	25 133			
1996	177,229	28,296	8.64%	12.59%	71.5%
1997	185,272	28,465	4.54%	0.60%	74.1%
1998	185,383	28,292	0.06%	-0.61%	74.8%
1999	188,216	28,308	1.53%	0.06%	75.9%
2000	194,909	29,786	3.56%	5.22%	74.5%
2001	196,581	30,573	0.86%	2.64%	73.4%
2002	204,895	31,608	4.23%	3.38%	73.8%
2003	211,984	31,509	3.46%	-0.31%	76.8%
2004	221,014	32,597	4.26%	3.45%	77.2%
2005	239,645	35,873	8.43%	10.05%	76.3%
2006	244,242	36,210	1.92%	0.94%	77.0%
Average Growth			3.42%	3.09%	75.0%

Appendix 1B – SA demand forecast (medium)

Year	Energy Demand (GWh)	Maximum Demand (MW)	Energy Growth Rate	Maximum Demand Growth Rate	Load Factor
2006	244 242	36 210			
2007	251,242	38,809	2.87%	7.18%	73.9%
2008	259,830	40,241	3.42%	3.69%	73.5%
2009	268,906	41,670	3.49%	3.55%	73.7%
2010	278,416	43,210	3.54%	3.70%	73.6%
2011	288,316	44,757	3.56%	3.58%	73.5%
2012	298,795	46,382	3.63%	3.63%	73.3%
2013	309,839	48,132	3.70%	3.77%	73.5%
2014	321,487	49,970	3.76%	3.82%	73.4%
2015	333,777	51,975	3.82%	4.01%	73.3%
2016	346,785	54,025	3.90%	3.94%	73.1%
2017	360,665	56,283	4.00%	4.18%	73.2%
2018	375,131	58,636	4.01%	4.18%	73.0%
2019	390,301	61,101	4.04%	4.20%	72.9%
2020	406,484	63,734	4.15%	4.31%	72.6%
2021	423,460	66,354	4.18%	4.11%	72.9%
2022	441,255	69,237	4.20%	4.35%	72.8%
2023	459,949	72,222	4.24%	4.31%	72.7%
2024	479,367	75,271	4.22%	4.22%	72.5%
2025	499,874	78,491	4.28%	4.28%	72.7%
2026	521,647	81,910	4.36%	4.36%	72.7%
Average Growth			3.87%	4.17%	73.1%

Source: NERSA 2005

Appendix B – LSM demographics and appliance ownership levels

Demographics and appliance ownership of the ten Living Standards Measure (LSM) groups					
LSM group	Population '000 (no of adults)	Average household income (p.m)	Location	House type	Appliances
LSM 1	1,062	R 1,080.45	Rural	Traditional hut	Minimal durables except radio sets
LSM 2	2,732	R 1,401.29	Rural	House/matchbox house	Minimal durables except radio and stove
LSM 3	2,953	R 1,794.81	Rural	Electrified House/matchbox house	Minimal durables except radio and stove
LSM 4	4,557	R 2,535.68	Rural	Electrified House/matchbox house	TV's, hi-fi/radios, electric hotplates, fridges
LSM 5	4,843	R 3,122.33	Rural	House	TV's, hi-fi/radios, electric hotplates, fridges
LSM 6	5,597	R 5,386.00	Urban	House	Ownership of a number of durables
LSM 7	2,957	R 8,667.33	Urban	House	Increased ownership of a number of durables
LSM 8	2,158	R 12,336.69	Urban	House	Full ownership of durables including DVD,PC and sat. dish
LSM 9	2,546	R 16,296.05	Urban	House	Full ownership of durables including DVD,PC and sat. dish
LSM 10	1,898	R 23,053.57	Urban	House	Full ownership of durables including DVD,PC and sat. dish

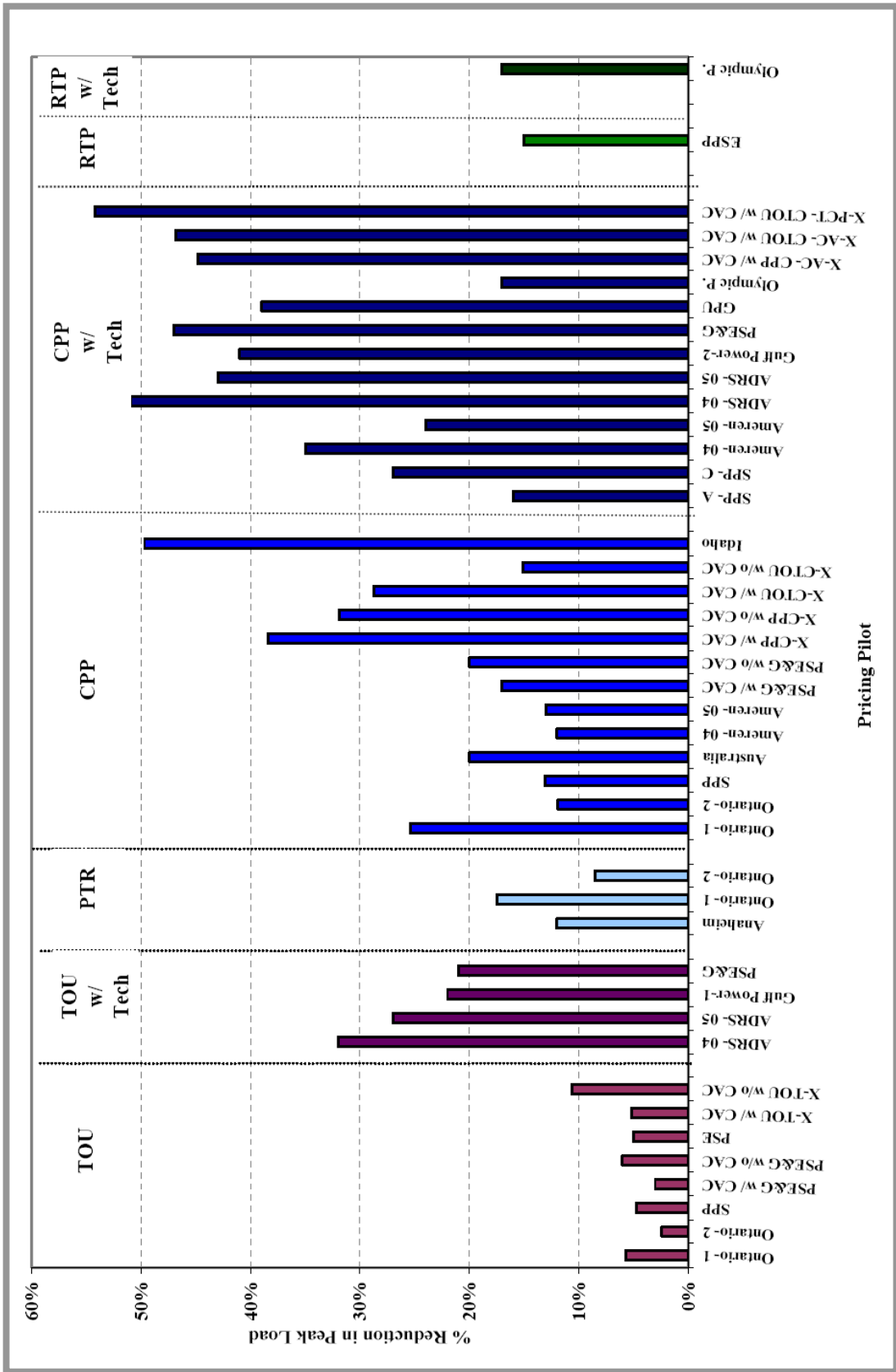
Source: South African Advertising Research Foundation, 2008.

Appendix C – Summary of price elasticity estimates for various international countries

Item	Country	Long run (LR)/ Short Run (SR)	Price Elasticity estimate	Time span	Electricity Price [USD] per kWh	Electric power consumption (kWh per capita)	GDP growth %(annual)	GNI per capita (current international \$)	World Bank rating
1	Kazakhstan ⁵	SR	-0.22	1994-2003	0.04	3234	3	4565	Upper middle income
2	USA ¹⁵	SR	-0.193	1978-1979	0.1	9653	2	-	High income: OECD
		LR	-1.403	1978-1979					
3	Namibia ⁹	LR	-0.298	1980-2002		1081	3	2707	Lower middle income
4	USA Texas, Louisiana ¹²	SR	-0.06 to -0.16	1970-1980	0.1	8717	3	12150	High income: OECD
		LR	-0.47 to -0.58	1970-1980					
5	Nigeria ²²	Both	Not significant: 0?	1970-1980	-	49	7	800	Low income
6	India ⁹	SR	-0.65	1985/86 to 1993/94	0.46	268	5	819	Lower middle income
7	India ¹³	SR	-0.3 to -0.5	1993-1994	0.46	336	6	1015	Lower middle income
8	Jamaica ²⁰	SR	Not significant: 0?	1970-86	-	761	1	2263	Upper middle income
		LR	Not significant: 0?	1970-86					
9	Sri Lanka ³	LR	0 to -0.063	1970-2003	-	156	4	1718	Lower middle income
10	Seoul (South Korea)		-0.2463	2005	0.1	7779	4	21240	Low income
11	California ²¹		-0.39	1993 and 1997	0.1	12 358	4	27456	High income: OECD
			< \$18000						
			>\$18k and < \$37k						
			>\$37k and < \$60k						
			>\$60k						
			< 4450 kWh						
			>4450 and < 6580 kWh						
			>6580 and < 9700 kWh						
			> 9700 kWh						
14	USA ⁶	SR	-0.2	1977-2004	0.1	11 591	3	25073	High income: OECD
		LR	-0.32						
15	Greece ¹¹	SR	-0.21	1961-86	0.1	1474	5	11229	High income: OECD
	Greece	LR	-0.58	1961-86					
16	Singapore ⁴	SR	-0.1	1972-1990	-	2886	8	11696	High income: OECD
		LR	-0.35						
17	Switzerland ¹⁴	LR	-0.3	1987-1990	0.1	7578	3	23155	High income: OECD
18	Norway ¹⁶	SR	-0.433	1976-1993	0.1	20945	3	14808	High income: OECD
		LR	-0.442	1976-1994	0.1	21119	3	15284	High income: OECD
19	South Africa ²⁶	LR	-0.011	1978-2005	0.05	4293	2	5722	Upper middle income
20	Bangladesh ²³	LR	-0.043	1973-1990	-	26	4	408	Low income
21	India ²⁵	SR	-0.65	1985/6-1993/4	0.46	268	5	819	Lower middle income
22	Greece ²³	SR	-0.21	1961-1986	0.1	1474	5	11229	High income: OECD
		LR	-0.58	1961-1987					
23	Taiwan (Chinese Taipei) ¹⁷	All	-0.15	1955-1995	0.079	-	-	-	-
24	Saudi Arabia ¹⁰	LR	-0.01	1980-92	-	3332	1	15137	High income: nonOECD
25	USA ²³	SR	not available	1949-1993.	0.1	8 541	3	21990	High income: OECD
		LR	0.5		0.1	10 740	3	21529	High income: OECD
26	USA ¹⁸			1973-1998					
27	GCC - Saudi Arabia:	SR	-0.04	1970-1997					
		LR	-1.24			2763	6	15617	High income: nonOECD
28	GCC - UAE	SR	-0.09	1970-1997					
		LR	-2.43			6519	6	37425	High income: nonOECD
29	GCC - Kuwait	SR	-0.08	1970-1997					
		LR	-1.1			7098	3	25815	High income: nonOECD
30	GCC - Oman	SR	-0.07	1970-1997					
		LR	-0.82			1286	7	9401	High income: nonOECD
31	GCC - Bahrain	SR	-0.06	1970-1997					
		LR	-3.39			5283	3	15069	High income: nonOECD
32	GCC - Qatar	SR	-0.18	1970-1997					
		LR	-1.09			8182	-	-	High income: nonOECD
33	Australia ¹	LR	-0.3388	1969-1998	0.1	6621	3	15374	High income: OECD

Adapted from: Heunis and Du Preez (2008)

Appendix D – Pricing pilots: participants’ responses



Source: Faruqui and Sergici (2008).

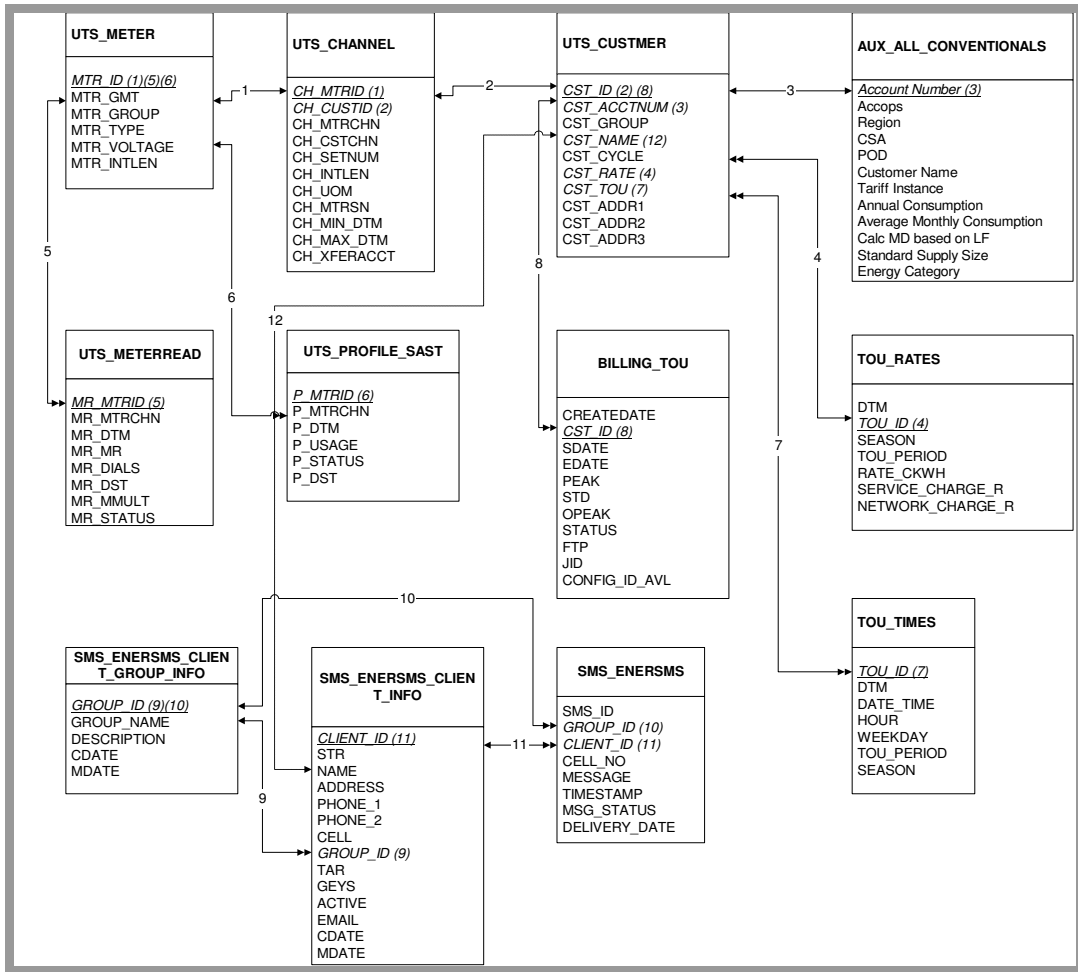
Appendix E1 – Sandton control and treatment customers – example of dataset

CST	CUS	GROU	T	N	MinR	Readin	eadin	MaxRe	g	ading	Order	Total				Daily				Daily						
												Total	OffPeak	Total	OffPeak	Total	OffPeak	Total	OffPeak	peak kWh	peak kWh	Daily	Monthly	weekend	Total	Total
P	UM	AvgReading	gCount	g	g	g	g	g	g	g	g	Peak kWh	weekday	kWh wkend	kWh	ave	Kp	Ko	total	average	ln(Kp/Ko)	ln(Pp/Po)	kWh	kWh	Total	Total
TOU2	1	2.315909091	330	0	7.03	1	764.25	2388.09	1270.78	3658.87	1474.373	11.58	36.18	47.76	1432.88	-1.14	1.41	48.876	238.814	97.752						
TOU2	2	3.832090909	330	0.31	8.87	2	1264.59	3052.93	1653.16	4706.09	1990.227	19.16	46.26	65.42	1962.51	-0.88	1.41	63.583	327.085	127.166						
TOU2	3	2.086121212	330	0.1	6.76	3	688.42	2399.11	1047.6	3446.71	1378.377	10.43	36.35	46.78	1403.42	-1.25	1.41	40.292	233.904	80.585						
TOU2	4	0.836090909	330	0.15	3.93	4	275.91	1757.86	815.66	2573.52	949.81	4.18	26.63	30.81	924.44	-1.85	1.41	31.372	154.073	62.743						
TOU2	5	1.634878788	330	0.26	5.07	5	539.51	1647.33	896.16	2543.49	1027.667	8.17	24.96	33.13	994.02	-1.12	1.41	34.468	165.670	68.935						
TOU2	6	3.947030303	330	0.19	9.81	6	1302.52	4323.54	1999.5	6323.04	2541.853	19.74	65.51	85.24	2557.30	-1.20	1.41	76.904	426.217	153.808						
TOU2	7	2.666212121	330	0.26	7.2	7	879.85	3038.62	1584.43	4623.05	1834.3	13.33	46.04	59.37	1781.12	-1.24	1.41	60.940	296.854	121.879						
TOU2	8	3.201878788	330	0.15	7.62	8	1056.62	3482.1	1738.53	5220.63	2092.417	16.01	52.76	68.77	2063.05	-1.19	1.41	66.867	343.842	133.733						
TOU2	9	3.970272727	330	0.85	11.86	9	1310.19	6519.03	2973.77	9492.8	3600.997	19.85	98.77	118.62	3558.74	-1.60	1.41	114.376	593.123	228.752						
TOU2	10	4.026666667	330	0.05	2.82	10	132.88	1307.51	653.77	1961.28	698.0533	2.01	19.81	21.82	654.72	-2.29	1.41	25.145	109.120	50.290						
TOU2	11	1.687727273	330	0.32	5.26	11	556.95	3632.7	1498.74	5131.44	1896.13	8.44	55.04	63.48	1904.39	-1.88	1.41	57.644	317.398	115.288						
TOU2	12	1.309	330	0.38	3.97	12	431.97	3079.42	1575.63	4655.05	1695.673	6.55	46.66	53.20	1596.09	-1.96	1.41	60.601	266.014	121.202						
TOU2	13	0.772939394	330	0	2.69	13	255.07	2466.2	961.75	3427.95	1227.673	3.86	37.37	41.23	1236.94	-2.27	1.41	36.990	206.157	73.981						
TOU2	14	1.106696967	330	0.31	2.31	14	365.21	1659.14	758.02	2417.16	927.4567	5.53	25.14	30.67	920.16	-1.51	1.41	29.155	153.360	58.309						
TOU2	15	1.125363636	330	1.83	9.57	15	2021.37	8508.38	4297.13	12805.51	4942.293	30.63	128.91	159.54	4786.25	-1.44	1.41	165.274	797.708	330.548						
TOU2	16	1.13830303	330	0.18	4.16	16	375.64	1893.42	1094.22	2987.64	1213.093	5.69	28.69	34.38	1031.39	-1.62	1.41	42.085	171.898	84.171						
TOU2	17	4.074181818	330	0.19	10.86	17	1344.48	4515.34	1937.33	6452.67	2599.05	20.37	68.41	88.79	2663.55	-1.21	1.41	74.513	443.926	149.025						
TOU2	18	8.645363636	330	0.75	19.85	18	2852.97	7074.86	3385.14	10460	4437.657	43.23	107.19	150.42	4512.65	-0.91	1.41	130.198	752.108	260.395						
TOU2	19	1.329181818	330	0.22	4.26	19	438.63	1745.44	989.54	2734.98	1057.87	6.65	26.45	33.09	992.76	-1.38	1.41	38.059	165.460	76.118						
TOU2	20	2.319606060	330	0.65	8.55	20	1054.7	3227.9	1714.06	4941.96	1998.887	15.98	48.91	64.89	1946.64	-1.12	1.41	65.925	324.439	131.851						
TOU2	21	3.847696967	330	0.56	8.83	21	1269.74	5261.06	2622.88	7883.94	3051.227	19.24	79.71	98.95	2968.55	-1.42	1.41	100.880	494.758	201.760						
TOU2	22	6.078787878	330	0.19	2.19	22	200.6	1796.27	719.99	2516.26	905.62	3.04	27.22	30.26	907.67	-2.19	1.41	27.692	151.278	55.384						
TOU2	23	2.776545455	330	0.19	5.35	23	593.59	2969.96	1481.08	4451.04	1681.543	8.99	45.00	53.99	1619.80	-1.61	1.41	56.965	269.966	113.929						
TOU2	24	2.927333333	330	0	9.19	24	966.02	3248.22	1725.72	4973.94	1979.987	14.64	49.22	63.85	1915.56	-1.21	1.41	66.374	319.261	132.748						
TOU2	25	4.783242424	330	0.85	9.13	25	1578.47	5867.58	2797.07	8664.65	3414.373	23.92	88.90	112.82	3384.57	-1.31	1.41	107.580	564.095	215.159						
TOU2	26	5.531606061	330	0.69	12.87	26	1825.43	6668.4	3131.94	9800.34	3875.257	27.66	101.04	128.69	3860.83	-1.30	1.41	120.459	643.472	240.918						
TOU2	27	4.824121212	330	0.64	9.87	27	1591.96	5532.98	2926.27	8459.25	3305.403	24.12	83.83	107.95	3238.61	-1.25	1.41	112.549	539.768	225.098						
TOU2	28	2.776545455	330	0.44	9.95	28	916.26	3982.18	2030.03	6012.21	2359.409	13.88	60.34	74.22	2226.56	-1.47	1.41	78.078	371.094	156.156						
TOU2	29	14.432151512	330	2.07	28.75	29	4762.61	15957.17	7850.71	23807.88	9523.497	72.16	241.78	313.94	9418.08	-1.21	1.41	301.950	1569.680	603.901						
TOU2	30	3.74030303	330	1.31	15.89	30	2422.3	6804.31	3068.58	9872.89	4098.397	36.70	103.10	139.80	4193.91	-1.03	1.41	118.022	698.986	236.045						
TOU2	31	1.398545455	330	0.11	4.61	31	461.52	1807.17	892.65	2699.82	1053.78	6.99	27.38	34.37	1031.22	-1.36	1.41	34.333	171.870	68.665						
TOU2	32	4.604923664	262	0.31	9.88	32	1206.49	5102.56	2221.53	7324.09	2843.527	23.02	97.14	120.17	3605.03	-1.44	1.41	111.077	600.838	222.153						
TOU2	33	2.480424242	330	0.27	5.62	33	818.54	3992.37	1620.9	5613.27	2143.937	12.40	60.49	72.89	2186.78	-1.58	1.41	62.342	364.463	124.685						
TOU2	34	2.980848485	330	0.5	8.93	34	983.68	3638.94	1800.26	5439.2	2140.96	14.90	55.14	70.04	2101.19	-1.31	1.41	69.241	350.198	138.482						
TOU2	35	4.926090909	330	1.01	9.99	35	1625.61	4514.97	2059.35	6574.32	2733.31	24.63	68.41	93.04	2791.17	-1.02	1.41	79.206	465.195	158.412						
TOU2	36	1.992181818	330	0.15	8.97	36	657.42	1947.05	917.02	2864.07	1173.83	9.96	29.50	39.46	1183.85	-1.09	1.41	35.270	197.308	70.540						
TOU2	37	1.275181818	330	0	6.86	37	420.81	2434.85	1184.57	3619.42	1346.74	6.38	36.89	43.27	1298.03	-1.76	1.41	45.560	216.338	91.121						
CON	1	5.851848485	330	1.28	12.47	38	1931.11	5588.96	2834.71	8423.67	3451.593	29.26	84.68	113.94	3418.21	-1.06	0.00	109.033	569.720	218.005						
CON	2	0.990242424	330	0	5.24	39	326.78	989.88	461.53	1451.41	592.73	4.95	15.00	19.95	598.48	-1.11	0.00	17.75	99.75	35.50						
CON	3	1.417333333	330	0	5.18	40	467.72	1408.27	1007.35	2415.62	961.133	7.09	21.34	28.42	852.72	-1.10	0.00	38.74	142.12	77.49						
CON	4	1.770151515	330	0.08	6.82	41	584.15	1551.36	856.46	2407.82	997.3233	8.85	23.51	32.36	970.69	-0.98	0.00	32.94	161.78	65.88						
CON	5	3.437484848	330	0.19	9.81	42	1134.37	2774.53	1694.96	4469.49	1867.953	17.19	42.04	59.23	1776.77	-0.89	0.00	65.19	296.13	130.38						
CON	6	4.536060606	330	0.85	10.81	43	1496.9	2902.28	1843.63	4745.91	2080.937	22.68	43.97	66.65	1999.63	-0.66	0.00	70.91	333.27	141.82						
CON	7	2.824757576	330	0.55	5.66	44	932.17	1746.18	999.37	2745.55	1225.907	14.12	26.46	40.58	1217.43	-0.63	0.00	38.44	202.91	76.87						
CON	8	3.532969697	330	0.16	8.19	45	1165.88	3448.31	1794.42	5242.73	2136.203	17.66	52.25	69.91	2097.36	-1.08	0.00	69.02	349.56	138.03						
CON	9	0.087575758	330	0	10.18	46	2008.9	5461.75	2548.57	8010.32	3339.74	30.44	82.75	113.19	3395.75	-1.00	0.00	98.02	565.96	196.04						
CON	10	6.097454545	330	1.8	9.81	47	2012.16	4782.64	2869.6	7652.24	3221.467	30.49	72.46	102.95	3088.55	-0.87	0.00	110.37	514.76	220.74						
CON	11	4.670909091	330	0.49	9.63	48	1541.4	3391.62	1725.78	5117.4	2216.26	23.3														

Appendix E2 – Tableview control and treatment customers – example of dataset

CUS	CST_G_T_N	ROUP	UM	AvgReading	Readin g	MinRe adin g	MaxR eadin g	Order	Wh	Total		Total off		Daily peak	Daily off peak	Daily average	Monthly average	In(Kp/Ko)	In(Pp/Po)	Daily weekend off	Total weekend	Total	Total
										Peak_k	Wh	OffPeak_k	OffPeak_kWh										
CON	1	2.834030303	330	0.83	7.52	1	935.23	2192.29	1172.57	3364.86	1121.62	14.17	33.22	47.39	1421.60	-0.85	0.00	45.10	236.93	90.20			
CON	2	1.501606061	330	0.02	5.44	2	495.53	965.91	432.21	1398.12	466.04	7.51	14.64	22.14	664.29	-0.67	0.00	16.62	110.72	33.25			
CON	3	2.909272727	330	0.44	8.16	3	960.06	2540.28	1339.41	3879.69	1293.23	14.55	38.49	53.04	1591.06	-0.97	0.00	51.52	265.18	103.03			
CON	4	1.187575758	330	0.09	5.35	4	391.9	903.39	525.42	1428.81	476.27	5.94	13.69	19.63	588.77	-0.84	0.00	20.21	98.13	40.42			
CON	5	1.341969697	330	0	5.81	5	442.85	873.09	448.78	1321.87	440.62	6.71	13.23	19.94	598.15	-0.68	0.00	17.26	99.69	34.52			
CON	6	0.893393939	330	0.11	3.62	6	294.82	795.59	501.62	1297.21	432.40	4.47	12.05	16.52	495.64	-0.99	0.00	19.29	82.61	38.59			
CON	7	1.224963636	330	0.29	3.18	7	404.04	1036.3	566.67	1602.97	534.32	6.12	15.70	21.82	654.70	-0.94	0.00	21.80	109.12	43.59			
CON	8	1.018545455	330	0.14	2.93	8	336.12	813.48	443.1	1256.58	418.86	5.09	12.33	17.42	522.55	-0.88	0.00	17.04	87.09	34.08			
CON	9	4.606545455	330	0.58	8.5	9	1520.16	2993.23	1564.6	4557.83	1519.28	23.03	45.35	68.38	2051.54	-0.68	0.00	60.18	341.92	120.35			
CON	10	1.586606061	330	0.23	5.67	10	523.58	1180.71	634.91	1815.62	605.21	7.93	17.89	25.82	774.68	-0.81	0.00	24.42	129.11	48.84			
CON	11	2.734030303	330	0.42	6.61	11	902.23	2160.6	971.76	3132.36	1044.12	13.67	32.74	46.41	1392.20	-0.87	0.00	37.38	232.03	74.75			
CON	12	3.047060606	330	0.31	8.8	12	1005.53	2046.46	1228.74	3275.2	1091.73	15.24	31.01	46.24	1387.27	-0.71	0.00	47.26	231.21	94.52			
CON	13	3.867393939	330	0.33	8.8	13	1220.14	2724.82	1984.74	4709.56	1569.85	18.49	41.29	59.77	1793.16	-0.80	0.00	76.34	298.86	152.67			
CON	14	1.992939394	330	0.12	6.87	14	657.67	2731.78	1323.84	4055.62	1351.87	9.96	41.39	51.36	1540.66	-1.42	0.00	50.92	256.78	101.83			
CON	15	5.150606061	330	0.07	9.81	15	1699.7	3357.51	1864.52	5222.03	1740.68	25.75	50.87	76.62	2298.73	-0.68	0.00	71.71	383.12	143.42			
CON	16	1.889787879	330	0.91	4.38	16	623.63	1467.57	879.05	2346.62	782.21	9.45	22.24	31.68	950.55	-0.86	0.00	33.81	158.42	67.62			
CON	17	2.171484848	330	0.37	4.57	17	716.59	1359.21	817.88	2177.09	725.32	10.86	20.59	31.45	943.55	-0.64	0.00	31.46	157.26	62.91			
CON	18	2.248696969	330	0.3	5.18	18	742.07	1484.75	745.22	2229.97	743.32	11.24	22.50	33.74	1012.19	-0.69	0.00	28.66	168.70	57.32			
CON	19	1.939696969	330	0.19	5.69	19	640.19	1327.98	809.88	2137.86	712.62	9.70	20.12	29.82	894.62	-0.73	0.00	31.15	149.10	62.30			
CON	20	2.523090909	330	0.24	6.61	20	832.62	1933.03	1138.74	3071.77	1023.92	12.62	29.29	41.90	1257.11	-0.84	0.00	43.80	209.52	87.60			
CON	21	1.621878788	330	0.29	4.37	21	535.22	1008.29	712.8	1721.09	573.70	8.11	15.28	23.39	701.60	-0.63	0.00	27.42	116.93	54.83			
CON	22	3.113818182	330	0.61	7.55	22	1027.56	2600.06	1167.3	3767.36	1255.79	15.57	39.39	54.96	1648.92	-0.93	0.00	44.90	274.82	89.79			
CON	23	1.896121212	330	0.05	7.09	23	625.72	1419.92	825.05	2244.97	748.32	9.48	21.51	30.99	929.84	-0.82	0.00	31.73	154.97	63.47			
CON	24	3.866424242	330	0.46	6.88	24	1117.52	2879.46	1826.18	4705.64	1568.55	16.93	43.63	60.56	1816.81	-0.90	0.00	70.24	302.80	140.48			
CON	25	1.503151515	330	0.02	8.54	25	496.04	1335.84	698.72	2034.56	678.19	7.52	20.24	27.76	832.67	-0.99	0.00	26.87	138.78	53.75			
CON	26	1.511878788	330	0.13	5.65	26	498.92	1260.11	714.08	1974.19	658.06	7.56	19.09	26.65	799.56	-0.93	0.00	27.46	133.26	54.93			
CON	27	1.592393939	330	0.16	5.04	27	525.49	1193.25	684.45	1877.7	625.90	7.96	18.08	26.04	781.25	-0.82	0.00	26.33	130.21	52.65			
CON	28	2.035090909	330	0.04	6.91	28	671.58	2524.84	1195.54	3720.38	1240.13	10.18	38.26	48.43	1452.92	-1.32	0.00	45.98	242.15	91.96			
CON	29	1.421727273	330	0.13	4.17	29	469.17	1117.32	654.1	1771.42	590.47	7.11	16.93	24.04	721.13	-0.87	0.00	25.16	120.19	50.32			
CON	30	2.756757576	330	0.38	9.12	30	909.73	2575.91	1345.28	3921.19	1307.06	13.78	39.03	52.81	1584.38	-1.04	0.00	51.74	264.06	103.48			
CON	31	1.960151515	330	0.06	6.24	31	646.85	1312.82	585.58	1898.4	632.80	9.80	19.89	29.69	890.76	-0.71	0.00	22.52	148.46	45.04			
CON	32	2.738818182	330	0.27	8.76	32	903.81	1954.25	885.98	2840.23	946.74	13.69	29.61	43.30	1299.12	-0.77	0.00	34.08	216.52	68.15			
CON	33	1.572424242	330	0.13	5.23	33	518.84	1009.27	797.4	1806.67	602.22	7.86	15.29	23.15	694.60	-0.67	0.00	30.67	115.77	61.34			
CON	34	2.409242424	330	0.19	4.57	34	795.05	2086.5	1066.15	3152.65	1050.88	12.05	31.61	43.66	1309.80	-0.96	0.00	41.01	218.30	82.01			
CON	35	2.753484848	330	0.23	6.37	35	908.65	2528.26	1239.16	3767.42	1255.81	13.77	38.31	52.07	1562.23	-1.02	0.00	47.66	260.37	95.32			
CON	36	1.259363636	330	0.08	4.37	36	415.59	1224.08	772.01	1996.09	665.36	6.30	18.55	24.84	745.30	-1.08	0.00	29.69	124.22	59.39			
CON	37	1.611818182	330	0.19	4.78	37	531.9	901.41	537.98	1439.39	479.80	8.06	13.66	21.72	651.50	-0.53	0.00	20.69	108.58	41.38			
CON	38	2.023181818	330	0.64	6.61	38	667.65	1748.24	893.21	2641.45	880.48	10.12	26.49	36.60	1098.13	-0.96	0.00	34.35	183.02	68.71			
CON	40	1.405939394	330	0.14	6.35	39	463.96	1928	996.38	2924.38	974.79	7.03	29.21	36.24	1087.25	-1.42	0.00	38.82	211.21	76.64			
CON	41	0.060151515	330	0	0.24	40	19.85	78	40.85	118.85	39.62	0.30	1.18	1.48	44.48	-1.37	0.00	1.57	7.41	3.14			
CON	42	2.531151515	330	0.2	6.2	41	835.28	1721.17	949.36	2670.53	890.18	12.66	26.08	38.73	1162.02	-0.72	0.00	36.51	193.67	73.03			
CON	43	0.819393939	330	0.1	4.55	42	270.4	653.02	425.4	1078.42	359.47	4.10	9.89	13.99	419.74	-0.88	0.00	16.36	69.96	32.72			
CON	44	3.2	330	0.36	6.94	43	1056	2159.52	1272.01	3431.53	1143.84	16.00	32.72	48.72	1461.60	-0.72	0.00	48.92	243.60	97.85			
CON	45	3.464363636	330	0.41	9.44	44	1143.24	2276.62	1465.28	3741.9	1247.30	17.32	34.49	51.82	1554.48	-0.69	0.00	56.36	259.08	112.71			
CON	46	1.081757576	330	0.12	3.63	45	356.98	679.95	366.45	1046.4	348.80	5.41	10.30	15.71	471.33	-0.64	0.00	14.09	78.56	28.19			
CON	47	3.500363636	330	0.26	8.46	46	1155.12	1965.4	863.84	2829.24	943.08	17.50	29.78	47.28	1418.42	-0.53	0.00	33.22	236.40	66.45			
CON	48	0.633	330	0.1	3.98	47	208.89	642.06	377.08	1019.14	339.71	3.17	9.73	12.89	386.80	-1.12	0.00	14.50	64.47	29.01			
TOU2	1	1.398636364	330	0.23	6.17	48	461.55	1870.85	1185.24	3056.09	1018.70	6.99	28.35	35.34	1060.18	-1.40	1.41	45.59	176.70	91.17			
TOU2	2	0.676030303	330	0.15	3.91	49	223.09	1315.27	649.16	1964.43	654.81	3.38	19.93	23.31	699.25	-1.77	1.41	24.97	116.54	49.94			
TOU2	3	1.357818182	330	0.1	5.36	50	448.08	1117.03	647.95	1764.98	588.33	6.79	16.92	23.71	711.41	-0.91	1.41	24.92	118.57	49.84			
TOU2	4	1.678424242	330	0.27	5.8	51	553.88	2154.11	913.3	3067.41	1022.47	8.39	32.64	41.03	1230.90	-1.36	1.41	35.13	205.15	70.25			
TOU2	5	1.670363636	330	0.17	5.02	52	551.22	1783.94	805.91	2589.85	863.28	8.35	27.03	35.38	1061.44	-1.17	1.41	31.00	176.91	61.99			
TOU2	6	1.699333333	330	0.19	6.38	53	560.78	1807.8	827.53	2635.33	878.44	8.50	27.39	35.89	1076.63	-1.17	1.41	31.83	179.44	63.66			
TOU2	7	0.819363636	330	0	4.85	54	26.85																

Appendix F1 – HomeFlex database relationship diagram



Source: Dekenah (2004)

Appendix F2 – HomeFlex database query for extracting panel data

```
SELECT
FROM      TOU_TIMES INNER JOIN
          UTS_PROFILE_SAST INNER JOIN
          Aux_all_conventionals INNER JOIN
          UTS_CHANNEL INNER JOIN
          UTS_METER ON UTS_CHANNEL.CH_MTRID = UTS_METER.MTR_ID
          INNER JOIN
          UTS_CUSTMER ON UTS_CHANNEL.CH_MTRID = UTS_CUSTMER.CST_ID
          ON
          Aux_all_conventionals.[Account Number] = UTS_CUSTMER.CST_ACCTNUM
          INNER JOIN
          TOU_RATES ON UTS_CUSTMER.CST_RATE = TOU_RATES.TOU_ID
          INNER JOIN UTS_METERREAD ON UTS_METER.MTR_ID =
          UTS_METERREAD.MR_MTRID ON UTS_PROFILE_SAST.P_MTRID =
          UTS_METER.MTR_ID ON
          TOU_TIMES.TOU_ID = UTS_CUSTMER.CST_TOU INNER JOIN
          BILLING_TOU ON UTS_CUSTMER.CST_ID = BILLING_TOU.CST_ID
```